Deutsche Bundesbank Eurosystem

Discussion Paper

Deutsche Bundesbank
No 29/2023

Effects of mergers on network models of the financial system

Daniel Nevermann
(Goethe-Universität Frankfurt)
Lotta Heckmann-Draisbach
(Deutsche Bundesbank)

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

ISBN 978–3–95729–964–2
ISSN 2941–7503

Non-technical summary

Research Question

Considering the consolidation trend among banks over the past years, and the deep need to better understand factors that influence stability of the financial system, we use a network model approach and aim to analyze the effect of mergers and acquisitions onto the stability of financial networks from a theoretical point of view.

Contribution

Based on financial network models, we perform an extensive analysis on effects of mergers and acquisitions on the stability of financial networks. We analyze the impact of mergers on the stability inter alia for different network structures, various rules of how merging parties are selected ("merger process") and different contagion channels.

Results

Our main finding is that merging activities can stabilize or destabilize the system, depending on various details such as the connectivity of the network and the assumed merge process. Merging activities can increase diversification of single banks and resilience to shocks. However, merging activities can also decrease stability, if e.g. the merge process creates new channels of contagion, or if unsufficiently stable banks emerge in key positions in the network. Our study thus indicates that it cannot be concluded in general whether merging activities benefit or decrease stability of single banks or the system, but that several aspects have to be considered.

Nichttechnische Zusammenfassung

Fragestellung

Wir greifen zwei Trends der letzten Jahre auf, die anhaltende Konsolidierung im Bankensektor einerseits und die Notwendigkeit, die Stabilität des Finanzsystems genauer zu verstehen andererseits, und analysieren mit Netzwerkmodellen den Einfluss von Fusionen auf die Stabilität des Finanzsystems.

Beitrag

In einer umfassenden theoretischen Analyse des Einflusses von Fusionen auf die modellierten Netzwerke betrachten wir unter anderem verschiedene Netzwerkstrukturen, verschiedene Regeln, wie fusionierende Banken ausgewählt werden, sowie verschiedene Ansteckungskanäle.

Ergebnisse

Fusionen können die Stabilität der untersuchten Netzwerke erhöhen oder verringern, je nachdem, wie stark das Netzwerk verbunden ist und wie der Fusionsprozess modelliert wird. Ein Zusammenschluss kann die Diversifizierung von Banken und die Widerstandsfähigkeit gegenüber Schocks erhöhen. Andererseits können neue Ansteckungskanäle oder eine Entstehung einer wenig stabilen Bank in einer für das System zentralen Position die Widerstandsfähigkeit des Netzwerks verringern. Unsere Studie weist darauf hin, dass Fusionen nicht per se positiv oder negativ auf die Stabilität einzelner Banken und auf das System wirken, sondern dass für eine Beurteilung eine detaillierte Betrachtung verschiedener Aspekte nötig ist.

Deutsche Bundesbank Discussion Paper No 29/2023

Effects of Mergers on Network Models of the Financial System*

Daniel Nevermann
Goethe-Universität Frankfurt

Lotta Heckmann-Draisbach
Deutsche Bundesbank

Abstract

Despite the ongoing consolidation trend in the banking industry and the attention some mergers (in particular between large banks) have been receiving, there is no consistent picture of the impact of mergers on the stability of the financial system. In this paper, we aim to provide a universal framework to study the generic effect of mergers and acquisitions on the resilience of financial systems based on different network models. We investigate the impact of a wide variety of model assumptions, e.g. connectivity, contagion channel and the merger process, on different static and dynamic stability measures. We provide a range of theoretical results highlighting the mechanisms that influence systemic risk in consolidated financial systems. Our main finding is that merger activities can stabilize or destabilize the modelled financial network, depending on various details such as the connectivity of the network and the assumed merger process. Merger activities can increase diversification of single banks and support their resilience to shocks, and may slow down contagious default. However, merger activities can also decrease stability if, for example, the network is driven into the contagion window or insufficiently stable banks emerge in key positions in the network.

Keywords: Financial network model, Mergers and Acquisitions, Financial Stability, Contagion

JEL classification: G01, G21.

---

*E-Mail: nevermann@itp.uni-frankfurt.de, lotta.heckmann-draisbach@bundesbank.de. The authors thank Barbara Drossel, Pedro Cuadros-Solas, Natalie Kessler, Thomas Kick, the participants of the research group seminar (Theory of complex systems, Darmstadt, January 2022), the participants of Bundesbank's research seminar (Frankfurt, October 2022) and the participants of the AFFI conference (Bordeaux, June 2023) for helpful comments. The views expressed in this paper are those of the author(s) and do not necessarily coincide with the views of the Deutsche Bundesbank or the Eurosystem.

1 Introduction

The global financial system has seen a consolidation trend for over four decades now (see e.g. DeYoung, Evanoff, and Molyneux (2009)) and the number of banks has been steadily declining. As it was observed that the decrease rate was even higher during the global financial crisis of 2007-2008, it could be conjectured that crises may even speed up consolidation (see Wójcik and Ioannou (2020)). Motives for mergers and acquisitions (M&A) can be diverse. Mergers can be stockholder value enhancing, cause efficiency improvements, lead to higher diversification, may be motivated by managers' hopes for higher compensation post merger or the goal of becoming a systemically relevant institution (see e.g. DeYoung et al. (2009)). A further aspect is regulatory interventions, as authorities might enforce the acquisition of a troubled institution by its more stable competitors.

While consolidation is thus an ongoing process in the banking sector which appears to be interrelated with crises, the effects of M&A activity on the stability of the financial system as a whole are not well understood. Some studies seek to tackle this topic from an empirical point of view; we will provide an overview of the relevant literature in Sec. 2. The few studies that employ network tools to investigate the effects of mergers and acquisitions on the stability of the financial system focus on specific cases (e.g. Rogers and Veraart (2013); Gaffeo and Molinari (2016)). Gaining more knowledge in this area would be desirable for several reasons: As mergers are an omnipresent feature of the interbank market, closely investigating the effects of M&A activity on the financial network, i.e. the changing bank numbers, the changing size distributions and the change in network structure is key to a better understanding of the development of the banking sector. Furthermore, a sound understanding of the effects of mergers could enable authorities to have a solid basis for decisions related to mergers, which ultimately may positively influence financial stability.

In this paper, we will investigate the effect of mergers on stylized financial networks with the primary goal to shed light onto the network theoretical mechanisms influencing systemic risk in financial systems undergoing M&A activity. Modeling the banking system as a network appears very natural: In modern financial systems, banks and other financial institutions, such as hedge funds and insurance companies, are highly interconnected directly through a web of claims and obligations, and indirectly through commonly held assets. Both connection types may affect banks, and the connections can be regarded as different network layers, thus leading to a multiplex network. In our analysis, we will therefore consider both the direct and the indirect channel. The basis of our investigations will be the financial contagion model by Gai and Kapadia (2010) for the direct channel and the model introduced by Caccioli, Shrestha, Moore, and Farmer (2014) for the indirect channel. As a new feature, we introduce mergers into the systems. We investigate different methods of selecting banks for mergers and compare a random selection of merging banks with a process that favors larger institutions to take part in the merger process. Furthermore, we analyse several static and dynamic stability measures and provide additional insight into the mechanisms that change the stability of the networks, thereby also extending the existing literature. We also perform several robustness checks to validate our results.

As a result, we are thereby able to show that merger activities can increase the stability of the model financial system if the initial connectivity is not too low or if one large stable bank emerges that can shield the network from shocks. For the latter case, we further examine the role of the large bank and show that its stability strongly determines the stability of the network. On the other hand, mergers can decrease the stability of weakly connected systems as the system may be driven into the contagion window. In this case, merger activities can extend and speed up contagious default across the network. Based on our comprehensive analysis, including different contagion channels, connectivities, network topologies, merger processes and measures of stability, we thus present a novel perspective and provide a systematic and broad overview over different mechanisms on how bank mergers can affect systemic risk.

The structure of this paper is as follows. In the next section we review the relevant literature, with a focus on studies on stability analysis of financial network models and on literature related to merger activities. Then, in section 3, the network models are introduced and the merger process is specified. We then show our results on how merger activities influence the stability of the considered networks in section 4 and discuss them with respect to relevant literature in section 5. Section 6 concludes.

2 Related Literature

In this section we give an overview of the most important literature related to the subject. We start with a general introduction on systemic risk, contagion channels and related network analysis, before then turning to mergers and acquisitions.

While it has been a research topic for several decades, there is still a deep need for understanding and an ongoing debate on the roots of *systemic risk* and *financial contagion*; see e.g. Allen and Gale (2000); Eisenberg and Noe (2001); Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015); Glasserman and Young (2015); Meuleman and Vander Vennet (2020). In this context, a network approach has been widely used, in particular to evaluate systemic risk and the stability of the system (for a review, see e.g. Hüser (2016)). Credit exposures on the interbank market can be conveniently represented as links in a network of financial intermediaries. A frequently used approach (e.g. Gai and Kapadia (2010); Gaffeo and Molinari (2015); Elliott, Golub, and Jackson (2014); Bluhm, Faia, and Krahnen (2014)) is to externally impose an initial failure on the interbank market, which implies that other institutions directly exposed to a failed bank suffer losses. As a consequence, these banks might be unable to meet their interbank obligations, leading to further failures. This mechanism can enable losses to spread via the network of direct interbank exposures, which is commonly referred to as the *direct contagion channel*. There are studies indicating that contagion via the direct channel alone is unlikely (see e.g. Upper (2011)). However, in a recent study, the authors show that direct interbank network connections were an important factor of contagion for bank failure risk during the Great Depression (Calomiris, Jaremski, and Wheelock (2022)). The *indirect channel*, on the other hand, captures more subtle links between financial institutions relating to overlapping portfolios. The main mechanism for contagion via the indirect channel is through fire sales of common assets (e.g. Caccioli et al. (2014); Poledna, Martínez-Jaramillo, Caccioli, and Thurner (2021)): If a troubled institution is forced to sell off assets, asset prices might quickly drop, imposing losses on other institutions holding the same asset. The indirect channel is hypothesized to have been the primary vector of contagion in the 2007-2008 financial crisis (see Upper (2011); Caccioli et al. (2014)).

Both channels may affect banks, and the connections can be considered as different network layers, thus leading to a multiplex network. Here, it is important to note that these channels are not independent of each other: A bank might be tempted to sell illiquid assets as a result of losses, or the fear of losses, via the direct contagion channel, or might be unable to meet its liabilities due to losses via the indirect channel (see Hüser (2016); Glasserman and Young (2015)). The interplay of both channels is a topic of current research. For example, Barnett, Wang, Xu, and Zhou (2022) show for the European banking market that the indirect network is denser and might be more relevant for default cascades for the majority of banks and for systemic risk, while the direct channel is still relevant for individual banks. Another study shows that in systems where both channels are present, the connectivity may be relevant for efficient intervention policies at times of crisis (Bernard, Capponi, and Stiglitz (2022)).

We now turn to *network models* of the financial system in more detail. In their seminal work, Gai and Kapadia (2010) introduce a simple interbank network model (financial contagion model by Gai and Kapadia (GK model)), where banks (nodes) with stylized balance sheets are connected via randomly chosen claims (links) against each other. In their model, if a bank fails, it defaults on all its interbank liabilities and thus can induce further defaults, potentially leading to system-wide cascades. The authors show that this simple model exhibits a robust-yet-fragile tendency, which inspired many subsequent analyses.

As an example, Caccioli, Catanach, and Farmer (2012) investigate the GK model on different topologies and asset distributions. They find that a scale-free topology, which has been reported for several banking systems (see e.g. Hüser (2016); Boss, Elsinger, Summer, and Thurner 4 (2004)) has a positive effect on the stability of the system if the initially shocked bank is chosen at random, but worsens stability dramatically if a highly connected bank is chosen. For a heterogeneous (power law) asset distribution, the contagion window is wider than for the homogenous distribution. Similar results are also found by Guan and Pollak (2016).

The GK model focuses on the direct interbank channel; however, there are also network approaches to model cascades that arise through common asset holdings. Caccioli, Farmer, Foti, and Rockmore (2015) extend the GK model by introducing a single common asset of which all banks hold some fraction in their balance sheets. Once a bank fails it fire sells all its illiquid assets, which causes a devaluation of the common asset. The extended model therefore allows to investigate the interplay between the direct and the indirect contagion channel. The authors find that the considered networks' direct channel is important, yet the combination of the two channels greatly amplifies cascades.

Other studies focus solely on the indirect channel; for instance Caccioli et al. (2014) introduce a bipartite network model of overlapping portfolios by modeling banks and assets as nodes, where links between banks and assets represent an investment of a bank into a certain asset. Upon default of a bank it fire sells its portfolio. As a consequence, the value of every asset in the bank's portfolio declines which affects other banks invested in the same asset. In the study, the authors investigate the stability of the network as a function of parameters such as market crowding and diversification, and are able to pinpoint the parameter space where cascades predominantly occur.

While network models are commonly used to analyse the stability of the financial system, to our knowledge there are only few studies considering the impact of M&A in this context. Before turning to those, let us first give a brief general introduction to the relationship between M&A and financial stability.

In general, the literature is inconclusive how M&A activity and thus higher banking market concentration affect financial stability and whether the *concentration-stability* or the *concentration-fragility* view is dominant. Smith (1984) argues that in low-concentration banking sectors, competition for deposits may generate instability within the banking system. Furthermore, supporters of the concentration-stability hypothesis argue that larger banks may increase loan portfolio diversification of the banking sector, e.g. they might be more likely to invest in foreign markets and thus increase geographical diversification, which can reduce risk (see Boyd and Prescott (1986)). Another argument states that large banks may increase profits which provides higher capital buffers to counter shocks (see e.g. Boyd, De Nicolo, and Smith (2004)). Last, a concentrated market may be easier to monitor, which would decrease the risk of system-wide cascades.

On the other hand, supporters of the concentration-fragility hypothesis argue that the existence of large institutions systematically increases systemic risk (e.g. Moch (2018)). Mishkin (1999) argues that very large banks may be tempted to take on risky investments, as they might be likely to be rescued by the government due to their systemic importance. Moreover, larger banks might demand higher loan interest rates. As a consequence, borrowers might be more likely to take on risky investments to compensate higher loan repayments (Boyd and De Nicolo (2005)). Note that other works (e.g. Montoriol-Garriga (2008)) suggest lower lending rates of larger banks. Beck, Demirgüç-Kunt, and Levine (2006) also raise the concern that larger banks might be more difficult to monitor as larger banks are more widely dispersed in terms of geography and business. There are further empirical studies in favor of the concentration-fragility hypothesis (De Nicolo and Kwast (2002); Uhde and Heimeshoff (2009); Weiß, Neumann, and Bostandzic (2014)). Finally, there are also studies bridging the two opposite perspectives. Bretschger, Kappel, and Werner (2012) indicate that both hypotheses could be supported by empirical data and that there are differences between high-income and low-income countries. In a study on the US market, Brealey, Cooper, and Kaplanis (2019) found that following mergers, banks do not seem to increase or decrease their individual level of risk in the long run, which indicates that any diversification effects are dissipated. They also found that the impact of mergers on systemic risk might have changed over time in the past. Calice, Leonida, and Muzzupappa (2021) finds that the impact of higher concentration depends on the level of concentration and deduces that an intermediate concentration may be optimal for financial stability. Dontis-Charitos and Leong (2023) found different effects for the relevance of mergers for systemic risk between US and Europe and also explored the effects of size of the involved parties. In a further study on the US market, Maslak and Senel (2023) put forward that the effect of mergers onto systemic risk might differ between crisis times and normal times. Furthermore, they found that larger banks' mergers were more consistent with the concentration-fragility hypothesis, while smaller banks' mergers seemed more consistent with the concentration-stability hypothesis.

In our study, we will also contribute to this debate as our results indicate that M&A activity can increase or decrease stability, depending on the exact set of circumstances (in terms of network connectivity and the merger process) and the measure of stability.

Let us now turn to the studies that analyse the impact of mergers on the stability of financial model networks. Rogers and Veraart (2013) focus on the direct interbank network and analyses under which conditions other banks have an incentive to rescue a troubled institution. The authors set up a framework and establish conditions under which a rescue consortium is formed. They also discuss a few explicit toy examples such as a ring network. In another study, Gaffeo and Molinari (2016) consider a small network of banks connected via the direct channel. Contagion is spread via a bail-in mechanism. The authors include three different topology altering processes: vertical merger (one large bank acquires smaller counterparties), horizontal merger (one bank is broken up, and its shares are evenly distributed over other institutions) and semi-horizontal merger (merger can only happen between two small banks). Claims on the interbank market are rearranged after every merger round using rules sensitive to banks size. In this setup, the authors find for a certain range of bank capitalization that the stability of the system increases under a vertical merger process.

Furthermore, Cheng and Zhao (2019) analyse a model for the interbank market similar to the GK model, where the authors discuss forced mergers as a possible intervention policy. The merging institutions are chosen by different micro- and macro-prudential regulation frameworks. The authors find that mergers are, within a certain regime of connectivity, a viable intervention policy, i.e. they increase stability compared to the unmerged network.

While the aforementioned former models study the impact of mergers on the stability of the system, they only focus on specific cases and leave several aspects open, i.e. they only consider direct connections between banks, restrict themselves on small networks, and assume specific merger processes. However, no comprehensive study of the impact of mergers on the stability of financial networks has been presented so far. In our study, we will try to fill those gaps: we study different merger processes on different network topologies where financial intermediaries are directly and/or indirectly connected, and measure stability by static and dynamic measures. Furthermore, we perform various robustness checks by altering parameters and assumptions.

Last, we will briefly touch upon a separate strand of literature that focuses on the question as to why banks participate in merger activities, a question which can also become relevant for the model setup. DeYoung et al. (2009) provide an overview of the literature on mergers and acquisitions of financial institutions and finds various motives. Studies on M&A activity inside and outside the U.S. find evidence that mergers are stockholder value enhancing and improve efficiency. Furthermore, Hannan and Pilloff (2009) show that cost-efficient banks tend to acquire more inefficient counterparts. Anderson, Becher, and Campbell II (2004) analyse large U.S. bank mergers and find that CEO compensation increases post-merger, which might be an incentive for bank managers. Lastly, mergers can enable a bank to increase its diversification, i.e. lead to bank portfolios that cover a wider range of geographies and types of products and investments (see Berger, Buch, DeLong, and DeYoung (2004)). On the other hand, Craig and Dinger (2008) show that mergers can lead to decreasing checking account rates and thus may negatively impact conditions for customers.

3 Modelling Approach

Our modelling approach leverages upon well-established models, namely, the model by Gai and Kapadia (2010) for the direct channel, the model by Caccioli et al. (2014) for the

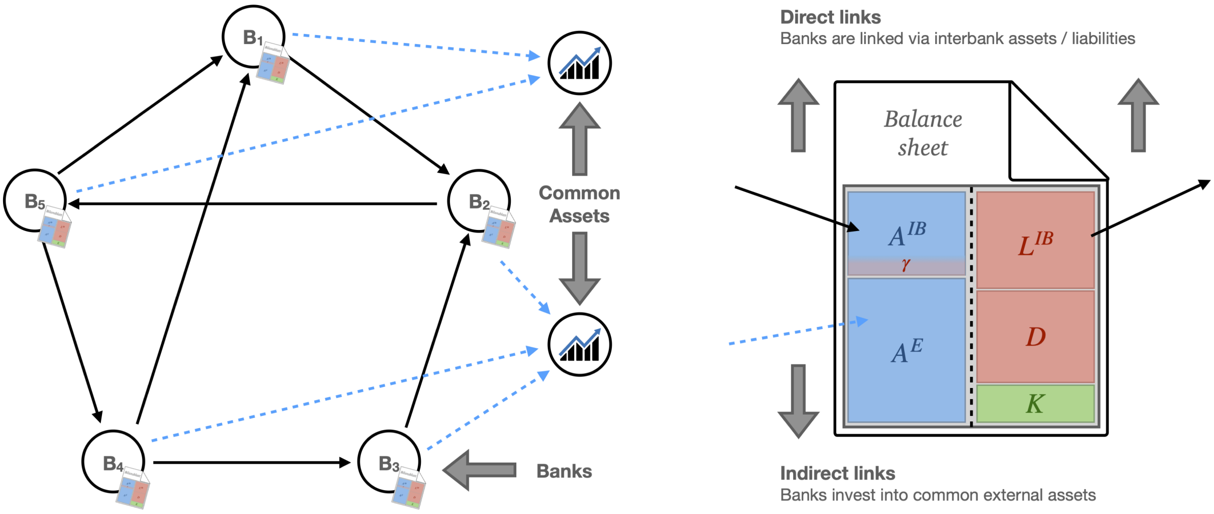

Figure 1: Setup of the network model, in an example with $n = 5$ and $m = 2$. Each bank is assigned a simplified balance sheet that contains the main positions: interbank assets, external assets, interbank liabilities, deposits, capital.

indirect channel, and the setup of the merging process developed by Gaffeo and Molinari (2016). We aim to stay close to established definitions, methods and parameters, also to facilitate comparison, as detailed in the following paragraphs.

3.1 Network model

The financial system is represented as a multilayer network comprising a set of financial institutions (banks for brevity, but it could also comprise other financial institutions) $\mathcal{B}$ and a set of commonly held assets $\mathcal{A}$. We consider random network structures[1], characterized by the average bank degree z, where the banks' degrees follow a Poisson distribution. The number of banks in the system is denoted by $n := |\mathcal{B}|$ and the number of commonly held assets by $m := |\mathcal{A}|$. Two types of links (i.e. two network layers) are present in the network: directed links between banks $i, j \in \mathcal{B}$, weighted by $\omega^{\mathrm{IB}}_{(ij)}$, represent interbank claims and obligations[2], while undirected links between a bank $i \in \mathcal{B}$ and a commonly held asset $a \in \mathcal{A}$, weighted by $\omega^{\mathrm{CA}}_{\{ia\}}$, represent a bank's investment into a certain asset. The weight represents the amount of monetary units of the interbank claim or investment, respectively.

Each bank $i \in \mathcal{B}$ is assigned a balance sheet. Balance sheets capture the financial state of the bank, i.e. its total assets A^{Σ}_i and total liabilities L^{Σ}_i, as well as the amount of shock the bank is facing at time t, resulting from losses on assets via the contagion channels $\gamma_i(t)$ and the bank's capital $K_i(t) := A^{\Sigma}_i - \gamma_i(t) - L^{\Sigma}_i$. The capital determines the solvency of a bank: We assume that if $K_i(t) \leq 0$, bank i is insolvent. The asset side is further subdivided into interbank assets A^{IB}_i, assets invested into the commonly held

[1]Note that we consider more realistic network structures as robustness checks.
[2]An outgoing link represents an obligation for a bank, i.e. money that the banks owes to a counterparty.

assets A_i^{CA} and external assets A_i^{E}, where the former two are given by

$$A_i^{\mathrm{IB}} := \sum_{j\in\mathcal{B}} \omega_{(ji)}^{\mathrm{IB}} \quad \text{and} \quad A_i^{\mathrm{CA}} := \sum_{a\in\mathcal{A}} \omega_{\{ia\}}^{\mathrm{CA}}$$

and A_i^{E} are assets external to the network. The relative importance of these asset positions is characterized by two parameters $\alpha^{\mathrm{IB}} := A_i^{\mathrm{IB}}/A_i^{\Sigma}$ and $\alpha^{\mathrm{CA}} := A_i^{\mathrm{CA}}/A_i^{\Sigma}$. As is common practice (see e.g. Gai and Kapadia (2010)), we assume that the interbank assets of each bank are evenly distributed over all counterparts[3]. The liability side, on the other hand, is subdivided into interbank liabilities L_i^{IB} and external liabilities L_i^{E}. Since every interbank asset is an interbank liability for a counterparty bank, the interbank liabilities are endogenously determined from the interbank assets. The capital in the banks' balance sheets is initially fixed by a parameter $\kappa_i := K_i(0)/A_i^{\Sigma}$. The general setup is shown in figure 1.

We consider two different contagion channels: For the direct channel of contagion, shock is spread over the web of interbank claims and obligations. As in Gai and Kapadia (2010), we make a zero recovery assumption, i.e. we assume that a defaulted bank is unable to repay any of its interbank liabilities[4]. Thus, every creditor of a defaulted bank is shocked by the full size of its loan. On the other hand, shock is spread over the indirect channel via overlapping portfolios. Each asset is assigned a price $p_j(t)$, where prices are initialized to one. Upon insolvency, a bank liquidates its asset portfolio, which causes a devaluation of the liquidated assets. As is common practice, devaluation is dictated by a market impact function f. For our analyses we consider two market impact functions that have also been used by other authors: First, $f_1(d_j) = \phi^{d_j}$, where $\phi \in [0,1]$ is a depreciation factor and d_j is the number of defaulted banks invested in asset j (see e.g. Sánchez (2017)). Second, $f_2(x_j) = \exp(-kx_j)$, where k is a constant and x_j is the fraction of asset j that has been liquidated (in accordance with Caccioli et al. (2014)).

We further consider two types of initial shock to the network which have also been employed in the literature: The perturbation is either induced by an initial bankruptcy of one bank in the network that then spreads the shock via the direct and indirect channel, or (for scenarios in which an indirect channel is present) via the initial devaluation of a network asset (toxic asset). The shock is then spread until the cascade terminates.

3.2 Mergers

We extend the network model by allowing banks to engage in M&A. In accordance with Gaffeo and Molinari (2016), mergers are performed in separate rounds, called *merger rounds* R. This allows us to distinguish and label states of the system. We merge two banks in the network i and j to a new bank k in a very natural way by first adding the external quantities in the balance sheets[5]. Afterwards, interbank links are combined such that the merged bank now owns the sum of all interbank claims and obligations of the previously separated banks. However, two cases deserve special attention: First, if the merging banks share a counterparty, the links to the same counterparty are joined into one,

[3]This could be interpreted as optimal diversification by banks.

[4]Note that we challenge this assumption as a robustness check.

[5]E.g. for liabilities $L_k^{\mathrm{E}} = L_i^{\mathrm{E}} + L_j^{\mathrm{E}}$.

which reduces the number of links. Second, if the merging banks have obligations between one another, these obligations are resolved at the time of the merger, which reduces the number of links and the amount of total assets in the system[6]. The investment portfolios, i.e. the links to commonly held assets, are also combined, which means that the merged bank invests in the union of the two previously separate portfolios. Note that we do not explicitly account for merger costs.

To summarize, in our model, the merger process changes the network in three key ways: the number of banks decreases, the interbank assets are rearranged in the mentioned way and the number of links and the total interbank assets may decrease through the merger process. We are aware that the reduction of merger activities to these mechanistic changes is a simplification, but the merger process is held simple and intuitive and we do not impose any additional assumptions on the merging parties; however, we will discuss later on the implications of these assumptions.

3.3 Simulation

To analyze the effects of mergers onto system stability, we start with an unmerged network with some initial degree $z_{R=0}$ and perform consecutive merger rounds while repeatedly measuring stability after each round. Our standard setup is a network of $n = 1000$ banks and a total of $R = 500$ merger rounds, which is motivated by the aim of a meaningful size of a financial market and a substantial change in the network through mergers[7]. For each simulation, we consider 1000 realizations of a network with a given connectivity $z_{R=0}$, over which we take an average. Note that the exact number of realizations should not influence the results as long as the number is high enough. An overview of the simulation parameters and their default vaules is given in Table 1. Stability is measured in terms of two widely used parameters: the *contagion frequency* is the probability that a system-wide cascade, i.e. a cascade where more than 5% of network assets default, occurs[8]. It is given by the fraction of realizations that show a system-wide cascade. The *contagion extent*, on the other hand, is given by the average fraction of defaulted system assets in realizations in which a system-wide cascade occurred.

We also analyse the impact of mergers on dynamic features of the system-wide cascade by measuring the (time) steps the cascade takes until it comes to a halt. Here, for convenience, we focus on the direct channel, where this measure can be understood as follows: In step 0, all banks are solvent. In step 1, we observe the first (initial) default of one bank. This can lead to further defaults of banks directly exposed to the defaulted bank, thus leading to further defaults in step 2, and so on. However, at some point, the cascade comes to a halt and no further defaults occur. We denote by CS (the *cascade steps*) the number of (time) steps until the cascade stops. This measure could be interpreted as an inverse average speed by which the cascade travels through the network, i.e. the higher CS, the slower the cascade propagates on average.

We consider two stylized processes to select banks for merging in each round that have also been employed by Gaffeo and Molinari (2016): in the *Random Merger Process (RMP)* we choose the merging partners at random and in the *Vertical Merger Process (VMP)*

[6]We check the implications of this procedure in robustness checks.

[7]We discuss this parameter choice in section 4.4 in more detail.

[8]The threshold is used as in Gai and Kapadia (2010).

one bank, in the following referred to as the acquiring bank, is selected as the merging institution and keeps acquiring other banks, thereby creating one dominant and highly interconnected bank in the system. While these two processes are quite stylized, we think that they can capture important and opposing features of merging activities and we discuss a possible extension of merger processes in section 4.4.

Table 1: Overview of relevant simulation parameters and procedures and their default choice.

Parameter	**Symbol**	**Benchmark**
Number of banks	$n = \lvert\mathcal{B}\rvert$	1000
Number of assets	$m = \lvert\mathcal{A}\rvert$	1000
Capital share compared to total assets	κ	0.04
Interbank asset share compared to total assets	α	0.2
Recovery rate	r	0
Mean degree	z	$[0, 10]$
Network realizations	$\lvert\mathcal{R}\rvert$	1000
Merger rounds (total)	R	500

4 Results

We consider three different scenarios which are briefly summarized in Table 2: In scenario (1) only a direct channel of contagion is present ($m = 0$). We choose $\alpha^{\mathrm{CA}} = 0$ and $\alpha^{\mathrm{IB}} = 0.2$ in accordance with Gai and Kapadia (2010). In scenario (2) both the direct and indirect channels are present, i.e. $\alpha^{\mathrm{IB}} = 0.2, \alpha^{\mathrm{CA}} = 0.02$. For simplicity we set $m = 1$ and assume that every bank in the network invests into this asset.[9] The shock is transmitted according to f_1[10]. And finally, in scenario (3), only an indirect channel is present, i.e. $\alpha^{\mathrm{IB}} = 0$, $m = 1000$ and $\alpha^{\mathrm{CA}} = 0.8$. The shock is transmitted according to f_2[11]. While other scenarios would be straightforward, the three selected configurations already provide a rich variety of results. The capital share is always set to $\kappa = 0.04$ as in Gai and Kapadia (2010).[12]

[9] This choice could also be interpreted as a simplified mean-field approach in which every bank suffers a similar average shock through devaluation of assets.

[10] In the simplified picture, where we only consider one asset in the network (mean-field approach), we further assume that the impact on the asset deprecation is independent of the bank size and thus use the market impact function f_1. We set $\phi = 0.3$ in accordance with Sánchez (2017)

[11] As done by other authors, we set $k = 1.0536$ such that an asset loses 10% of its value when 10% of holdings have been liquidated.

[12] Note that, for better comparability, the default parameter values are chosen similar to existing studies, which in turn are often inspired by corresponding values in real financial networks. In numerous robustness checks, we varied the parameter values.

Table 2: Overview of scenarios considered in the analysis.

Scenario	**Description**
(1)	Only the direct contagion channel (DCC) is present.
(2)	The direct and indirect contagion channels are present.
(3)	Only the indirect contagion channel (ICC) is present.

4.1 Financial network models prior to mergers

Before turning our attention towards mergers, we show the reproduced results for the unmerged network that have previously been found in the literature, e.g. Gai and Kapadia (2010); Caccioli et al. (2015); Sánchez (2017). In Figure 2, the contagion extent (CE) and contagion frequency (CF) are plotted over the average degree z.

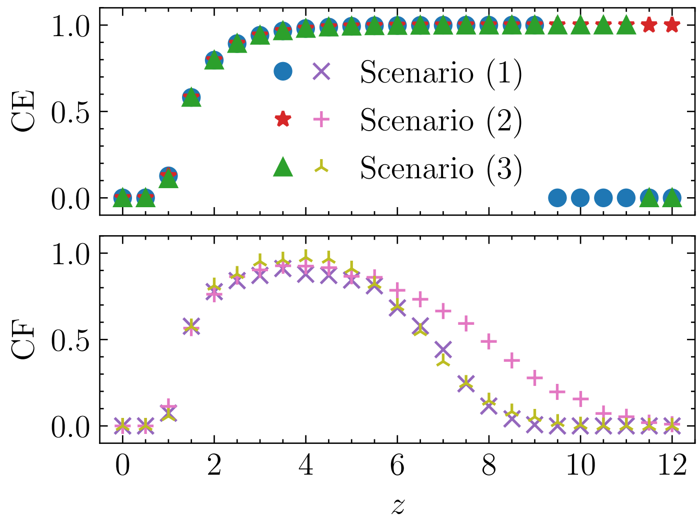

Figure 2: Contagion Extent (CE) and Contagion Frequency (CF) over average degree z for all considered scenarios (see table 2). For scenario (3) (only indirect channel), the shock is induced via an initial bankruptcy.

Instability is observed within a certain window of the average degree z, the contagion window. Below this window, for small values of z, the network exhibits many small connected components which are weakly or not at all linked. An initial shock is only spread within the respective connected component and therefore does not affect the vast majority of banks in the network. For large values of z, above the contagion window, banks diversify their assets such that they are able to withstand a few counterparty defaults, thus rendering cascades very unlikely. Towards the upper end of the contagion window, the system exhibits a robust-yet-fragile tendency in accordance with Gai and Kapadia (2010). System-wide cascades are very unlikely, but they cause a complete network collapse if they occur. The picture is broadly similar in all three scenarios. We also note that the interplay of a direct and indirect channel (scenario (2)) causes the most unstable networks.

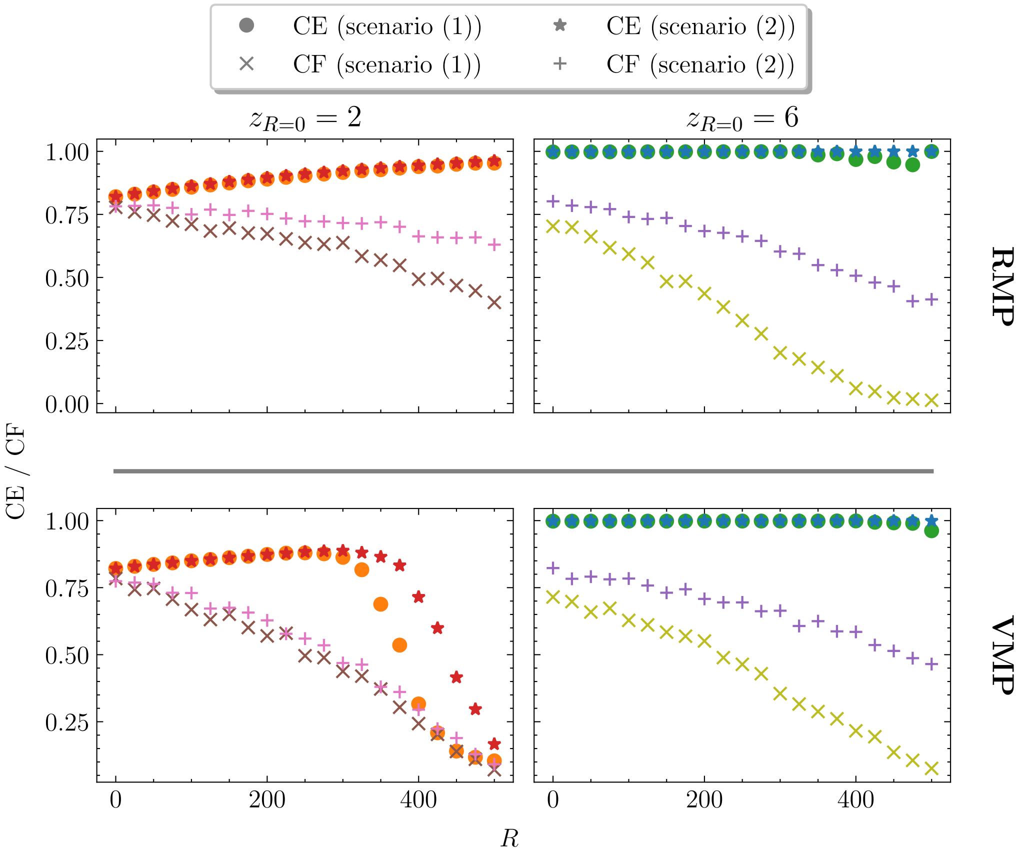

Figure 3: Results for scenarios (1) (only direct channel) and (2) (indirect and direct channels). Contagion Extent (CE) and Contagion Frequency (CF) are plotted over merger rounds R for the Random Merger Process (RMP) (top row) and the Vertical Merger Process (VMP) (bottom row).

4.2 Financial network models with mergers

We now include mergers in the network. In Figure 3, the results for scenarios (1) and (2) are shown for the random and the vertical merger process for two different initial connectivities which are chosen at the lower end and towards the upper end of the contagion window, respectively. We plot the contagion extent and contagion frequency over the merger rounds R. First, consider scenario (1), where only a direct channel is present. A shock is induced via the default of a randomly selected bank in the network. For the random merger process, we observe that the contagion frequency decreases over the merger rounds, while the contagion extent stays constant or increases, depending on initial connectivity. Since the network is sparse ($z \ll n$), most of the randomly selected merge partners are neither interconnected, nor share common neighbors. Therefore, mergers increase the diversification of merged banks - this is particularly the case for the initially denser network (right column of Figure 3). Although it is possible for a bank to participate in more than one merger, this occurs only randomly under the random merger process and the network prevails overall similar to the initial homogeneous state[13]. The

[13]In this case, stability trends mostly agree with the contagion window observed in the unmerged system, considering that the average degree z roughly doubles over the 500 merger rounds.

increased diversification through mergers increases the ability of merged banks to stop cascades in the early stages, hence the contagion frequency decreases. However, banks are not sufficiently diversified to stop a rolling cascade and thus the contagion extent is not impacted.

For the vertical merger process, similar to the random merger process, we observe a decrease of the contagion frequency in scenario (1), but also a decrease of the contagion extent after some merger rounds, in particular for the sparser network (left column of Figure 3). These stability changes can be attributed to the acquiring bank. Through consecutive mergers, this bank becomes more and more the center point of the network. Particularly for the initially denser network, the acquiring bank is connected to almost the entire network after 500 merger rounds.[14] During this process, it becomes more and more stable and acts as a cascade barrier in the network. After some point, the acquiring bank becomes stable enough to even absorb larger shocks in the event of system-wide cascades, thereby stopping a system-wide cascade and decreasing the contagion extent. The point where the acquiring bank starts to survive, even if a system-wide cascade occurs, coincides with the point where the contagion extent decreases.[15]

Next, we consider the addition of an indirect channel, i.e. scenario (2). A shock is again induced via the random default of a bank in the network. For the random merger process we observe that the contagion frequency increases if we include an indirect channel, compared to scenario (1). The effect is particularly visible for the higher connectivity. This can be understood as follows: As discussed above, the random merger process stabilizes systems, at least in part, by causing increased diversification of interbank loans. Through the additional indirect channel banks are gradually weakened by losses on the common external asset, thus decreasing their capital, which renders banks more susceptible to direct contagion and relativizes the benefits of increased diversification. For the vertical merger process we observe that the contagion frequency is higher if we add an indirect channel, but only for the initially denser network - the $z_{R=0} = 2$ network is unaffected. Furthermore, the point where the contagion extent decreases is pushed to higher merger rounds. The reason why the contagion frequency in the $z_{R=0} = 2$ is nearly unaffected by the additional indirect channel is that in the vertical merger process all banks except one remain unmerged. The indirect channel, through the market impact function, induces higher losses particularly at the start of the cascade, which increases counterparty risk for otherwise sufficiently diversified banks. In the sparse $z_{R=0} = 2$ case, interbank asset diversification is weak anyway and banks are typically vulnerable to a single counterparty default; the effect of the additional indirect channel onto the contagion frequency is thus weak. For the initially denser network, however, banks are more diversified and can typically (without the indirect channel) withstand counterparty defaults; here, we thus observe an effect through the indirect channel. To sum up the results from scenario (2), the introduction of an additional contagion channel can, compared to the original network,

[14]This is of course an extreme, and also an extremely stylized process and should not be understood as mimicking real merger activities. Rather, the aim is to explore the ultimate impact of merger activities under the assumptions detailed above.

[15]Here we would like to emphasize that the setup of our analysis implies that the share of risky assets on a bank's balance sheet can only decrease through merger activities, while the share of capital may increase if interbank links are eliminated through merger activities. This may seem to introduce a bias in our analysis towards a higher stability of merged banks. However, we analyze the impact of this assumption in the robustness checks.

naturally only decrease stability. It depends, however, on the network structure in terms of connectivity and on the merger process whether the indirect channel impacts stability or whether stability is unchanged.

To further investigate the additional instabilities of the indirect channel, we now consider the results for scenario (3), where only an indirect channel is present, in Figure 4. The top row shows the stability metrics over R for the random merger process and the bottom row for the vertical merger process. In this scenario, as the relevant links in the network are established between banks and assets, but we do not model direct links between banks, we distinguish between two different mechanisms to induce a shock: either via a defaulted bank or via a toxic asset.[16]

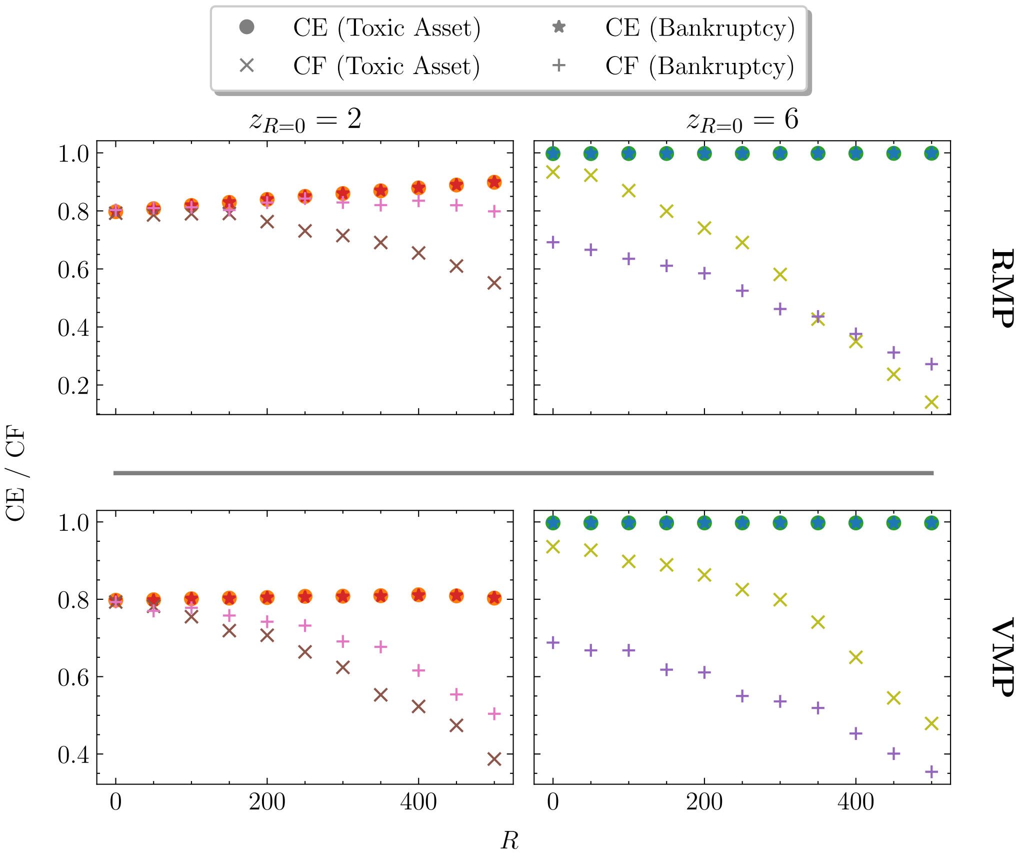

Figure 4: Results for scenario (3) (only indirect channel). The Contagion Extent (CE) and the Contagion Frequency (CF) are plotted over the merger rounds R for the Random Merger Process (RMP) (top row) and the Vertical Merger Process (VMP) (bottom row).

We first focus on the top row, where the results for the random merger process are detailed. For both initial connectivities, we observe a net decrease of the contagion frequency, however, the effect of mergers seems to be stronger if the shock is induced via a toxic asset in the system. The contagion extent increases or is unaffected by the mergers. The reason for the net decrease of the contagion frequency is again the increased diversification caused by the random merger process. Through the mergers, the investment

[16] In the toxic asset case, the initially devalued asset is chosen randomly, and its value is reduced by 35%.

portfolios of the merged banks increase in size, which reduces the importance of a single asset. On the other hand, merged banks pose a greater risk for the system if they are distressed. The random merger process typically increases portfolio sizes and investment volumes, which are associated with a higher market impact risk. Since we do not see any stabilization trends in the contagion extent, we deduce that merged banks are not capable of surviving a system-wide cascade. The reason that the effects of mergers are stronger in the case of a toxic asset in the system is again related to the increased diversification. First, it must be noted that initially shocking a randomly chosen asset must not cause any defaults in the network if banks invested in the initially shocked asset are able to absorb the depreciation. If average diversification increases, the probability that the initial depreciation is absorbed also increases. Second, while the average bank degree roughly doubles over the merger process, the average asset degree stays constant or even slightly decreases in accordance with our model setup. Hence, the impact of an initial bankruptcy increases, while the impact of initial asset depreciation stays constant or decreases, and potentially might be absorbed by diversified banks.

Next, we focus on the vertical merger process, i.e. the bottom row in Figure 4. Again, we observe a stabilization trend in the contagion frequency over the merger rounds. The contagion extent is mostly unaffected. Through the vertical merger process, the acquiring bank heavily increases its portfolio size (number of different assets in the portfolio) as well as the average investment per asset in the portfolio. As a consequence, the acquiring bank concentrates a high market impact through the large investment volumes and additionally excels at absorbing shocks thanks to its strong diversification. This can, in this stylized setting, reduce the risk of system-wide cascades. If, however, a cascade does break out, the acquiring bank is almost always pushed into default, which then has catastrophic consequences for the rest of the system. Therefore, we see a destabilization trend in the contagion extent. Again we observe that the network is more stable if the shock is induced via a toxic asset in the network, for reasons already discussed above.

4.3 Mergers and dynamics of default

To shed further light on the mechanisms behind the changes in stability, we now turn to the impact of mergers on the *dynamic* features of default cascades. In the unmerged system, the cascade steps are closely related to the contagion window as shown in Figure 5. Outside the contagion window no cascade occurs, so CS is set to 0, but could also be considered undefined. At the borders of the contagion window ($z \approx 2$ and $z \approx 9$), we can see that the resulting cascades are very slow (high number of cascade steps). Compared to the fastest cascades which are observed for $z \approx 4.5$, for $z \approx 1.5$, cascades need up to three times the number of time steps in order to travel through the network.

When introducing mergers, the resulting evolution of cascade steps over merger rounds is shown in Figure 6. We find that inside the contagion window, for an initial connectivity of $z_{R=0} = 6$ (right panel), the cascade steps increase as the number of merger rounds rises for both the random merger process and the vertical merger process. This is notable as, for these cases, we have seen that the contagion extent (CE) was nearly unchanged over the merger rounds (see right panel of Figure 3). Thus, while approximately the same extent of the network is affected by the cascade, nevertheless, we see that mergers influence the dynamics and reduce the propagation speed of contagious default.

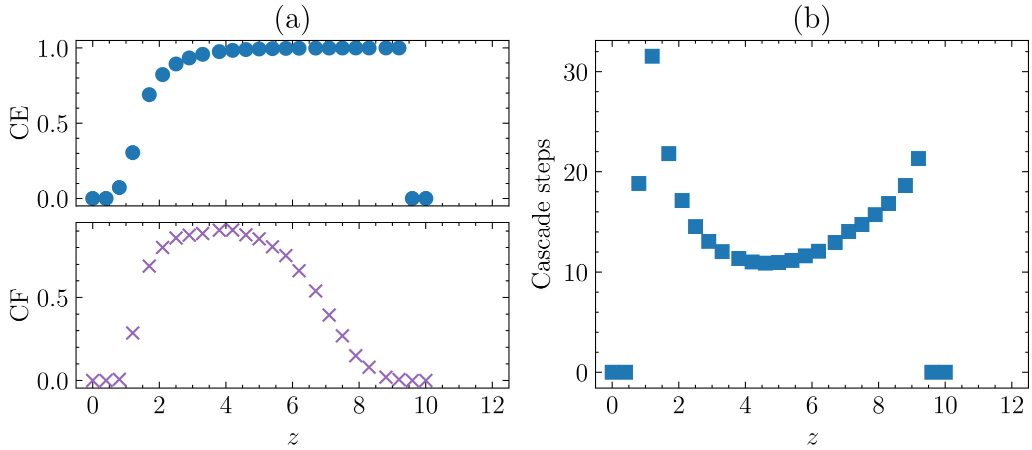

Figure 5: To the right (b), the number of cascade steps is plotted over the connectivity z in the unmerged system in scenario (1). For comparison, we show the respective contagion window on the left hand side (a).

For $z_{R=0} = 2$, we observe for the random merger process that the cascade steps decrease, thus implying faster cascades for increasing merger rounds. At the same time, we had seen that the contagion extent increases (see top-left part of Figure 3). For this configuration, mergers thus lead to both more extended and faster cascades and thus to a twofold destabilization of the network. In contrast, in the vertical merger process, starting from $R = 0$, mergers increase the cascade steps and thus slow down the cascade. The cascade steps reach a maximum at $R \approx 350$ and then decrease. Compared to the bottom-left plot of Figure 3, this is the point where the contagion extent begins to drastically decrease. The decrease in the cascade steps is thus in this case linked to a decrease in the contagion extent.

4.4 Robustness checks

As noted above, due to the simplicity of the models used, the results can in general not be easily transferred to concrete, real financial systems, but should rather be seen as general theoretical insights into possible mechanics of the impact of merger activities on financial networks. In this section, we challenge the generality of our theoretical results, by varying assumptions and parameters.

As a first robustness check, we vary the numeric parameters of the model. The initial model setup contains a choice for different parameter values (see Table 1) which could of course be changed. A variation of the relevant parameters (e.g. portion of interbank assets, capital) has also been performed in previous studies (e.g. Gai and Kapadia (2010)) and we see similar trends here, which is why we summarize them in brief: An increase in capital in general increases stability, while an increase in the risky assets decreases stability. These observations appear very natural and even mechanistic. However, we checked that the main results of our study relating to the impact of merger activities on stability remain unchanged in response to a variation of these parameters if kept in a meaningful range.

A second robustness check concerns the topology: One assumption in the network

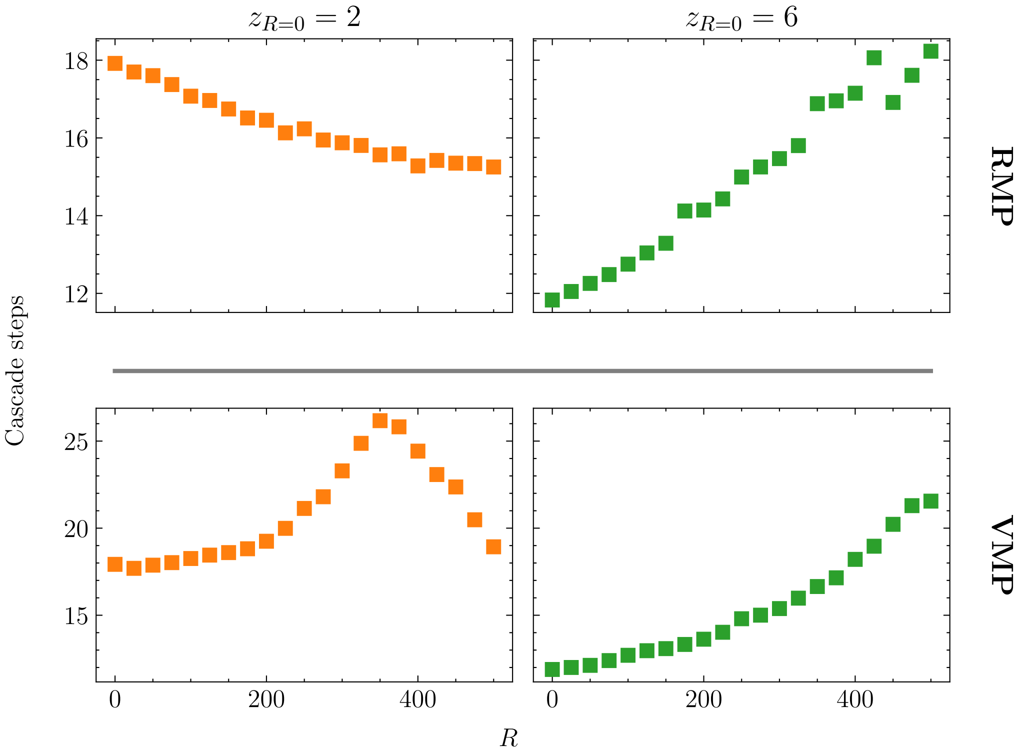

Figure 6: Cascade steps for scenario (1) (only direct contagion channel) over merger rounds R for the Random Merger Process (RMP) (top row) and the Vertical Merger Process (VMP) (bottom row) for $z_{R=0} = 2$ (left) and $z_{R=0} = 6$ (right).

models presented above is that of a random network structure. However, note that the GK model is very flexible regarding the underlying network structure and has also been used to explore the impact of different topologies (e.g. Caccioli et al. (2012)). There are studies reporting real interbank markets to have a scale-free degree distribution, e.g. Boss et al. (2004); Bech and Atalay (2010). Thus, to challenge the dependency on the network structure, we repeat the simulations with a scale-free topology. For this, we use scale-free networks according to the algorithm introduced by Chung and Lu (2002). We find that the scale-free topology benefits stability compared to the random topology if the bank initially defaulted is selected randomly; however, if we instead apply a targeted shock to a hub bank, system stability worsens drastically.[17] The general stability implications of mergers that we saw in random networks remain the same in Chung-Lu scale-free networks (scale-free networks). Here, we would like to state that while the structure of a scale-free network may appear more realistic, we chose to present our main results based on the random network structure. This is mainly because the scale-free network initially already contains a few hub banks, which makes interpretation of the role of these banks less obvious. In random networks, these hub banks only emerge and show their particular role during the merging process, which we consider more clear-cut.

A further robustness check concerns the zero recovery assumption and the assumption of permanent asset devaluation: In the direct channel, a bank defaults on all of its interbank liabilities and in the indirect channel, any asset devaluation is considered to be

[17] For unmerged networks this has previously been found e.g. in Caccioli et al. (2012).

permanent. While these assumptions seem simplistic and rather strong, a relaxation does not provide any surprising insights. This conclusion has previously been drawn for unmerged systems by Gai and Kapadia (2010). We repeated our simulations with a relaxed assumption: If banks can recover part of their claims against a defaulted bank, stability naturally increases. However, this is similar to decreasing the portion of interbank assets present on the banks' balance sheets (i.e. changing $\alpha = 0.2$ to a smaller value). Similarly, allowing a devalued asset to increase its value would be equivalent to reducing the effect of the market impact function or to reducing the portion of external common assets.

A less obvious assumption to challenge is the development of interbank assets and capital in the direct channel. As described above, through the mechanic merger process, interbank claims can disappear if two banks connected by a link merge. In this case, the (risky) interbank assets are reduced while the remaining balance sheet is unchanged. This implies that merged banks may have a comparative advantage over unmerged banks, as the ratio between their capital and their total assets may (mechanically) increase if their total assets decrease through the described process. To challenge this assumption, we performed additional simulations where we correct, after each merger round, for the potentially lost interbank assets, such that the ratio between capital and interbank assets stays constant. The stability trends are identical to the results shown above; we are therefore confident that this detail does not influence our conclusions.

It could further be perceived as restriction of our study that we only consider two merger processes, namely the random and the vertical merger process. Here, note that we performed additional selective analyses with the semi-horizontal merger process, which was analyzed in Gaffeo and Molinari (2016) and in which only unmerged parties are selected for merging - this process could thus in some sense be considered as the opposite of the vertical merger process. However, in our setup, the semi-horizontal merger process starts with a network of 1000 banks of size 1 and ends up with a network of 500 banks of size 2, yielding quite predictable results. We concluded that the results were of limited interest for the analysis of real merger processes.

Last, we should mention that our network size (1000 banks) is to some extent arbitrary, but of a meaningful size. To give some figures for comparison, e.g. Eurostat (2021) published for 2020 a number of 5400 banks operating in the EU. For its Member states, the numbers are smaller, with around 1500 for Germany and numbers well below 1000 for the other Member states. For the US, the FDIC (2023) published a number of around 5000 banks and saving institutions for 2020. The number of merger rounds (500) is chosen such that it results in meaningful variation of network size and structure. Our choice of $n/2$ merger rounds results in an average of one merger participation per bank and thus generates substantial changes in the network structure and stability metrics. In addition, note that the German banking sector underwent a similar consolidation trend within a period of ten years according to numbers of the Deutsche Bundesbank (2013).

5 Discussion

To analyze how the stability of the banking system can be affected by the consolidation trend, we consider different established network models of the financial system and extend them to include M&A. We also consider qualitatively different merger processes, where the processes differ by the selection of merge partners. Although these models are very

Table 3: Overview over our main results for the different scenarios detailed in Table 2 and for the Random Merger Process (RMP) and Vertical Merger Process (VMP). A "+" denotes a stabilizing impact of mergers, while "−" denotes a destabilizing impact of the mergers. CE: Contagion Extent, CF: Contagion Frequency.

	Effect	Scenario (1)	Scenario (2)	Scenario (3)
RMP	−	low connectivity: CE increases	low connectivity: CE increases	low connectivity: CF and CE increase (for bankruptcy)
RMP	+	high connectivity: CF decreases	high connectivity: CF decreases slightly	high connectivity: stronger effect for toxic asset
VMP	−	if default of dominating bank	if default of dominating bank	if default of dominating bank
VMP	+	low connectivity and sufficiently large R	low connectivity and even larger R	CF decreasing for large R (but CE constant)

stylized, they allow for valuable insights into how stability of financial networks may be altered by the modeled M&A activity.

Our goal is to capture the key channels of contagion in financial systems as well as their interplay: the direct channel and the indirect channel. The direct channel refers to losses on the interbank market due to defaults on loans and therefore captures counterparty risk for the banks in the system. For the indirect channel, one key connection is overlapping portfolios.

Our main result is that the impact of merger activities on system stability is diverse and depends on several aspects. In some constellations, mergers can benefit stability, while in others, it is detrimental. A concise overview over our findings is presented in Table 3. Particularly for the random merger process, stability outcomes show a sensitive dependence on the initial connectivity: While for highly connected systems the increased diversification caused by the mergers leads to more stable systems[18], weakly connected systems tend to show a destabilization trend in terms of an increased contagion extent and an increased cascade speed. For the vertical merger process we find a stabilization trend in cascade probability, irrespective of the initial connectivity. Also the cascade speed is generally reduced with an increasing number of merger rounds. The cascade extent, on the other hand, is unaffected or increases initially but then may decrease for large merger rounds. While these findings would in general support the concentration-stability hypothesis, this dramatically changes if the dominant bank, formed through consecutive vertical mergers, is attacked. Its default leads to a sudden system breakdown. We find that these results hold true both for a random and a scale-free network topology. Our results regarding the partially stabilizing effect of mergers are mostly consistent with earlier findings in the literature. Gaffeo and Molinari (2016) also find a stabilizing effect of vertical mergers in small networks modeling the direct channel. Although Cheng and Zhao (2019) consider different merger processes, they also find a stabilizing effect of mergers in

[18] In this work, sufficient diversification is generally regarded as a driver of stability. Other authors, however, note that if many banks in the system diversify into similar activities, the resulting homogenization of the system may increase the likelihood of contagion spillovers (Wagner (2008)).

some range of the connectivity.

The literature suggests that indirect connections between banks are of particular importance for the stability of the system (e.g. Upper (2011); Poledna et al. (2021)). In our simulations, we find that particularly the stability of networks resistant to shocks through diversification via the direct channel is negatively impacted by this additional channel and that the effect is even stronger in (the more realistic) scale-free networks than in random networks. For both merger processes we look at here, the random and the vertical merger process, the additional indirect channel reduces the partial positive effects of mergers on stability. This shows the importance of looking at different contagion channels. However, mergers can still increase the stability compared with the unmerged system under some circumstances.

For a network subject solely to the indirect channel, we find that mergers generally can benefit stability; however the effect is weaker than in the GK model. For the random merger process the stability outcome is again more sensitive to initial connectivity than for the vertical merger process. We further find that, in merged systems, the initial idiosyncratic default of a bank is potentially more harmful to the system than the sudden devaluation of a toxic asset. However, as discussed above, this is also partly due to the assumptions employed in the present model. Nevertheless, we think it is worth mentioning that the source of the initial shock (either one initially defaulting bank, which is a huge shock to one single bank, or a devalued asset, leading to a less intense shock to multiple banks) may impact different networks differently.

In the scope of our rather stylized modeling approaches we can formulate the following results that are common to our different modeling approaches: First, in sufficiently connected systems, mergers seem to increase the stability of financial systems and may thus potentially be an effective intervention policy. The mergers of small and medium-sized banks can benefit stability, but only for certain network topologies. The acquisition of smaller banks by their larger competitors was observed to increase stability by reducing the probability that contagion occurs at all and by increasing the steps needed to reach contagion through the network. In this sense, the merger of a small troubled institution with a stable (larger) bank in the system could be considered a viable resolution strategy according to our simulations. However, and very importantly, this holds true only if the survival of the larger bank is ensured. Our results show that the robustness of the emerging large bank is key, which also supports existing measures such as the G-SII/O-SII buffers which are aimed to ensure that large banks have a sound capital base.

While our analysis is able to give some model-based insights into the effects of mergers, thereby extending the sparse literature on the effects of M&A on systemic stability, we are also well aware of the limitations and shortcomings of the current approach.

While we base our analysis on random and scale-free topologies, there is also some evidence that real interbank markets may exhibit a core-periphery structure (see e.g. Fricke and Lux (2015)). In a core-periphery network, banks are partitioned into two sets based on their relations with each other. Core banks are connected to each other and to periphery banks, but periphery banks are not connected to each other. A core-periphery structure can arise in an interbank network, if lending relationships between banks are not directly bilateral, but rather pass through banks acting as intermediaries. This is observed in the German interbank market by Craig and Von Peter (2014), to name one example. An investigation of the effects of M&A on a core-periphery network could be an interesting extension to our investigations. In particular, we think it might be useful to analyze the vertical merger process, when considering a couple of core banks in the role of the acquiring bank(s), and potentially incorporating contagion dynamics between them. Additionally, it could be valuable to explore the impact of different types of mergers, namely core-core, core-periphery or periphery-periphery bank mergers.

While we did investigate the interaction of the direct and indirect channel, we limited ourselves to a rather simplistic case. We expect, however, that the destabilization trend compared to only directly linked networks, which we saw from our simplistic approach, would occur in a similar way. Furthermore, we expect that the stabilizing effects through diversification, but also the (de)stabilizing effects through centralization would be observed in a similar way. Nevertheless, an exploration of the possible interactions between the indirect and the direct channel of contagion in more detail might merit separate research. A further point to mention here is that we assume a simplified structure for the direct interbank network: all banks distribute their claims evenly and we do not assume any further distinction between claims. However, Aldasoro and Alves (2018) show for large European banks that the direct interbank network itself may already be considered as a multilayer network when distinguishing different instruments and maturities and thus contains a much higher complexity than assumed in this study.

Another detail is that we neither explicitly accounted for merger costs nor increasing efficiencies through mergers. One reason is to keep the model simple - merger costs/benefits would introduce additional parameters that would need to be estimated and set in a reasonable range. Another is that we think that, due to the simple nature of the models, introducing these features would not yield any surprising results: Merger activities would be systematically more stabilizing or destabilizing, depending on the choice of parameters. However, we acknowledge that this feature is not present in our analysis.

While we analysed different merger processes, the implementation of merger activities contains to a large extent a random element - in particular, we did not attempt to merge banks for which a merger is, for instance, optimal in a specific sense (apart from the assumption that the acquiring bank in the vertical merger process is seeking to grow). This modeling choice could be interpreted such that banks do not have any information to decide whether a merger is favorable for them (or for the network). It would certainly be an interesting extension to analyse strategic mergers where merging partners are chosen under certain selection rules (e.g. Rogers and Veraart (2013)).

A common feature of all models considered in this work is that they are static with regard to the network structure. The reasoning behind this assumption is simplicity, but also the idea that merging banks continue to pursue their activities similarly to their pre-merger business. This would be a reasonable assumption for banks that intend a strategic portfolio extension with their merger, for instance. Another interpretation would be that we assume that banks do not have time to rebalance their portfolio before failing. These points motivate that banks react neither to mergers nor to defaults. It could be an interesting yet more complex addition, however, to allow banks to rebalance their asset portfolio and interbank market connections as a reaction to defaults and mergers. However, to note that this requires additional assumptions on how the merged bank (and possibly all other banks) will reallocate their exposures among their potential counterparts. It is not clear that these additional assumptions will finally be more realistic than the static assumption, but we acknowledge that our results are certainly influenced by this assumption.

Other than that, we note that, despite our efforts to motivate our parameter choices with empirical data and the choices in previous studies, the various model parameters would further allow for possible calibration to concrete real-world financial systems (e.g. size distribution of banks, number of counterparties/external assets per bank etc.), to some extent. While this could be an interesting extension, we think that such investigations would wrongfully suggest a non-existent similarity of the analyzed models with real financial networks. In contrast, we are convinced that the more general analysis performed in this work makes the best use of the simplified stylized models and allows for an easy and meaningful interpretation.

Finally, it must be noted that all results in this work are purely theoretical. The use of stylized models in general is a strong simplification, which can still provide interesting insights into possible mechanisms. As we have seen in these simplified systems, mergers can improve or worsen system stability, depending on the connectivity and size of the merge partners, the overall size and degree distribution of the network and the contagion source and channel. These general insights can provide a basis for additional, more targeted research to support or contradict the observed features in more elaborated models or in real financial systems.

6 Conclusion

Motivated by the ongoing general consolidation trend in the banking sector and the increasing attention of merger activities, on the one hand, and the high importance of network models for analyzing the stability of financial systems, on the other hand, we aim to shed light on the effects of mergers on the stability of financial network models. A sound understanding of the effects of mergers on the stability of the financial system can provide important additional information to market participants and supervisors, and might support decision processes of authorities supervising the financial sector and monitoring M&A activity.

Using different well-established network models of the financial system enriched with M&A, we find that, in the stylized models under consideration, mergers can improve or worsen system stability, depending on a variety of details such as the connectivity and size of the merge partners, the overall size and degree distribution of the network and the contagion source and channel.

In weakly connected systems, merger activities can destabilize the network by driving the network into the contagion window, thereby increasing the contagion extent and increasing the speed by which the cascade propagates through the network. However, in these systems, the emergence of a large and highly connected bank can stabilize the system if this bank itself is stable. In more dense networks, mergers can increase stability by decreasing the contagion frequency and slowing down contagious cascades. We also showed that different measures of stability may provide different insights into the stabilizing and destabilizing mechanisms.

In our view, the rich variety of our results on theoretical and simplified models should be taken as a motivation to gain a deeper understanding of the impact of merger activities on the financial system.

References

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015). Systemic risk and stability in financial networks. *American Economic Review 105*, 564–608.

Aldasoro, I. and I. Alves (2018). Multiplex interbank networks and systemic importance: An application to European data. *Journal of Financial Stability 35*, 17–37.

Allen, F. and D. Gale (2000). Financial contagion. *Journal of Political Economy 108*(1), 1–33.

Anderson, C. W., D. A. Becher, and T. L. Campbell II (2004). Bank mergers, the market for bank CEOs, and managerial incentives. *Journal of Financial Intermediation 13*(1), 6–27.

Barnett, W. A., X. Wang, H.-C. Xu, and W.-X. Zhou (2022). Hierarchical contagions in the interdependent financial network. *Journal of Financial Stability 61*, 101037.

Bech, M. L. and E. Atalay (2010). The topology of the federal funds market. *Physica A: Statistical Mechanics and its Applications 389*(22), 5223–5246.

Beck, T., A. Demirgüç-Kunt, and R. Levine (2006). Bank concentration, competition, and crises: First results. *Journal of Banking & Finance 30*(5), 1581–1603.

Berger, A. N., C. M. Buch, G. DeLong, and R. DeYoung (2004). Exporting financial institutions management via foreign direct investment mergers and acquisitions. *Journal of International Money and Finance 23*(3), 333–366.

Bernard, B., A. Capponi, and J. E. Stiglitz (2022). Bail-ins and bailouts: Incentives, connectivity, and systemic stability. *Journal of Political Economy 130*(7), 1805–1859.

Bluhm, M., E. Faia, and J. P. Krahnen (2014). Monetary policy implementation in an interbank network: Effects on systemic risk. *SAFE Working Paper*.

Boss, M., H. Elsinger, M. Summer, and S. Thurner 4 (2004). Network topology of the interbank market. *Quantitative finance 4*(6), 677–684.

Boyd, J. H. and G. De Nicolo (2005). The theory of bank risk taking and competition revisited. *The Journal of Finance 60*(3), 1329–1343.

Boyd, J. H., G. De Nicolo, and B. D. Smith (2004). Crises in competitive versus monopolistic banking systems. *Journal of Money, Credit and Banking*, 487–506.

Boyd, J. H. and E. C. Prescott (1986). Financial intermediary-coalitions. *Journal of Economic theory 38*(2), 211–232.

Brealey, R., I. Cooper, and E. Kaplanis (2019). The effect of mergers on us bank risk in the short run and in the long run. *Journal of Banking & Finance 108*, 105660.

Bretschger, L., V. Kappel, and T. Werner (2012). Market concentration and the likelihood of financial crises. *Journal of Banking & Finance 36*(12), 3336–3345. Systemic risk, Basel III, global financial stability and regulation.

Caccioli, F., T. A. Catanach, and J. D. Farmer (2012). Heterogeneity, correlations and financial contagion. *Advances in Complex Systems 15*(supp02), 1250058.

Caccioli, F., J. D. Farmer, N. Foti, and D. Rockmore (2015). Overlapping portfolios, contagion, and financial stability. *Journal of Economic Dynamics and Control 51*, 50–63.

Caccioli, F., M. Shrestha, C. Moore, and J. D. Farmer (2014). Stability analysis of financial contagion due to overlapping portfolios. *Journal of Banking & Finance 46*, 233–245.

Calice, P., L. Leonida, and E. Muzzupappa (2021). Concentration-stability vs concentration-fragility. new cross-country evidence. *Journal of International Financial Markets, Institutions and Money 74*, 101411.

Calomiris, C. W., M. Jaremski, and D. C. Wheelock (2022). Interbank connections, contagion and bank distress in the Great Depression. *Journal of Financial Intermediation 51.*

Cheng, X. and H. Zhao (2019). Modeling, analysis and mitigation of contagion in financial systems. *Economic Modelling 76*, 281–292.

Chung, F. and L. Lu (2002). Connected components in random graphs with given expected degree sequences. *Annals of Combinatorics 6*(2), 125–145.

Craig, B. and G. Von Peter (2014). Interbank tiering and money center banks. *Journal of Financial Intermediation 23*(3), 322–347.

Craig, B. R. and V. Dinger (2008). Bank mergers and the dynamics of deposit interest rates. *Bundesbank Discussion Paper 2*, 1–28.

De Nicolo, G. and M. L. Kwast (2002). Systemic risk and financial consolidation: Are they related? *Journal of Banking & Finance 26*(5), 861–880.

Deutsche Bundesbank (2013). Banking stastistics.

DeYoung, R., D. D. Evanoff, and P. Molyneux (2009). Mergers and acquisitions of financial institutions: A review of the post-2000 literature. *Journal of Financial services research 36*(2-3), 87–110.

Dontis-Charitos, P. and S. Leong (2023). Bank consolidation, connectedness, and systemic risk.

Eisenberg, L. and T. H. Noe (2001). Systemic risk in financial systems. *Management Science 47*(2), 236–249.

Elliott, M., B. Golub, and M. O. Jackson (2014). Financial networks and contagion. *American Economic Review 104*(10), 3115–53.

Eurostat (2021). Number of banks decreasing.

FDIC (2023). Fdic bank data & statistics.

Fricke, D. and T. Lux (2015). Core–periphery structure in the overnight money market: evidence from the e-MID trading platform. *Computational Economics 45*(3), 359–395.

Gaffeo, E. and M. Molinari (2015). Interbank contagion and resolution procedures: inspecting the mechanism. *Quantitative Finance 15*(4), 637–652.

Gaffeo, E. and M. Molinari (2016). Macroprudential consolidation policy in interbank networks. *Journal of Evolutionary Economics 26*(1), 77–99.

Gai, P. and S. Kapadia (2010). Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences 466*(2120), 2401–2423.

Glasserman, P. and H. P. Young (2015). How likely is contagion in financial networks? *Journal of Banking & Finance 50*, 383–399.

Guan, Y. and M. Pollak (2016). Contagion in heterogeneous financial networks. *Advances in Complex Systems 19*(01n02), 1650001.

Hannan, T. H. and S. J. Pilloff (2009). Acquisition targets and motives in the banking industry. *Journal of Money, Credit and Banking 41*(6), 1167–1187.

Hüser, A.-C. (2016). Too interconnected to fail: A survey of the interbank networks literature. Technical report, Leibniz Institute for Financial Research SAFE.

Maslak, G. D. and G. Senel (2023). Bank consolidation and systemic risk: M&a during the 2008 financial crisis. *Journal of Financial Services Research 63*(2), 201–220.

Meuleman, E. and R. Vander Vennet (2020). Macroprudential policy and bank systemic risk. *Journal of Financial Stability 47*(C).

Mishkin, F. S. (1999). Financial consolidation: Dangers and opportunities. *Journal of Banking & Finance 23*(2-4), 675–691.

Moch, N. (2018). The contribution of large banking institutions to systemic risk: What do we know? a literature review. *Review of Economics 69*, 231–257.

Montoriol-Garriga, J. (2008). Bank mergers and lending relationships. *ECB Working Paper* (934).

Poledna, S., S. Martínez-Jaramillo, F. Caccioli, and S. Thurner (2021). Quantification of systemic risk from overlapping portfolios in the financial system. *Journal of Financial Stability 52*, 100808. Network models and stress testing for financial stability: the conference.

Rogers, L. C. G. and L. A. M. Veraart (2013). Failure and rescue in an interbank network. *Management Science 59*, 882–898.

Smith, B. D. (1984). Private information, deposit interest rates, and the 'stability' of the banking system. *Journal of Monetary Economics 14*(3), 293–317.

Sánchez, P. C. (2017). Financial contagion in the interbank market.

Uhde, A. and U. Heimeshoff (2009). Consolidation in banking and financial stability in europe: Empirical evidence. *Journal of Banking & Finance 33*(7), 1299–1311.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability 7*(3), 111–125.

Wagner, W. (2008). The homogenization of the financial system and financial crises. *Journal of Financial Intermediation 17*(3), 330–356.

Weiß, G. N., S. Neumann, and D. Bostandzic (2014). Systemic risk and bank consolidation: International evidence. *Journal of Banking & Finance 40*, 165–181.

Wójcik, D. and S. Ioannou (2020). Covid-19 and finance: Market developments so far and potential impacts on the financial sector and centres. *Tijdschrift voor economische en sociale geografie 111*(3), 387–400.