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Four Essays in Interbank Market and Blockchain : Design and Implementation of a Multi-Agent Architecture for the Blockchain-based Interbank Money Market

Morteza Alaeddini

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THÈSE

Pour obtenir le grade de

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Quatre essais sur le marché monétaire interbancaire et la blockchain : une approche multi-agents

Four Essays on Interbank Money Market and Blockchain: A Multi-agent Approach

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FOUR ESSAYS ON INTERBANK MONEY MARKET AND BLOCKCHAIN: A MULTI-AGENT APPROACH

DISSERTATION
submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
in Management Science

by
Morteza Alaeddini

École doctorale Science de Gestion
Université Grenoble Alpes

Grenoble, December 1st, 2022

PREFACE

I, Morteza Alaeddini, confirm that the work presented in this dissertation is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

This research was funded by the Initiative d'excellence (Idex) Université Grenoble Alpes under grant C7H-LXP11A95-IRSMMI. All the work described in this dissertation was carried out at the Centre d'Etudes et de Recherches Appliquées à la Gestion (CERAG) and the Laboratoire d'Informatique de Grenoble (LIG), under the supervision of Dr. Paul Reaidy, Prof. Philippe Madiès, and Prof. Julie Dugdale. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others except as specified in the text and summarised in the Statement of Contributions.

This dissertation is not substantially the same as any that I have submitted or is being concurrently submitted for a degree or diploma or other qualification at Université Grenoble Alpes or any other university or similar institution except as declared in Chapters 2–5. It does not exceed 100,000 words, including footnotes, tables, figures, bibliography, and appendices.

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Words cannot express my gratitude to my supervisors, Dr. Paul Reaidy, Prof. Philippe Madiès, and Prof. Julie Dugdale, for their invaluable patience and feedback. Paul Reaidy advised and helped me in all matters, both scientific and administrative, and more than just a mentor, he was always a kind friend. I owe all the knowledge I have acquired in this research in financial economics to Philippe Madiès for all the guidance and encouragement he gave me. In addition to guiding me in working with agents and relevant issues, Julie Dugdale made the biggest contribution to my manuscripts' readability and acceptance in various conferences and journals by carefully reviewing and editing them and giving excellent feedback. I could not have undertaken this journey without my defence committee, who generously provided knowledge and expertise. Additionally, this endeavor would not have been possible without the generous support from the Initiative d'excellence (I dex) Université Grenoble Alpes, who financed my research.

I would like to extend my sincere thanks to Dr. Önder Gürcan from the CEA LIST laboratory for helping me understand blockchain better and fixing logical bugs in my UML models. I am also thankful to Prof. Pierre Six from the NEOMA Business School for his detailed review of my last essay and his precious comments that gave me avenues to continue this research. I am also grateful to my friends in the CERAG and LIG laboratories for their academic assistance, stress relief, and moral support. Thanks should also go to the administrative staff of the two laboratories, especially Ms. Florence Alberti, Ms. Coralie Lucatello, and Ms. Françoise Jeewoath, who always helped me in sending formal requests, conference registrations, arranging for travel, and arranging payment for my travel invoices.

Lastly, I would be remiss in not mentioning my family, especially my spouse, Mahdiah, and my parents. Thank you, Mahdiah, for all your love and constant support. Thanks are also due to my parents for their unceasing encouragement, support, and attention. Your belief in me kept my spirits and motivation high during this process.

To my Guru, Dr. Noor-Ali Tabandeh

*“Imagination is more important than knowledge.
Knowledge is limited. Imagination encircles the world.”*

Albert Einstein

ABSTRACT

Due to its multi-disciplinary nature to link the topics of the interbank market, blockchain technology, and multi-agent simulation, this dissertation consists of four essays that, according to the JEL¹ classification, fall under the broad banners of financial institutions and services (G2); monetary policy, central banking, and the supply of money and credit (E5); information, knowledge, and uncertainty (D8); and mathematical and simulation modeling (C6).

Through a bibliometric analysis of 609 scientific documents as well as a detailed review of 160 recent studies, the first essay identifies the most significant factors influencing market players' strategies. It indicates elements that affect central banks' strategies in reducing systemic risk and preventing financial contagion, as well as managing the interbank network in a way that makes it more stable and resilient to shocks to conserve market confidence. It also addresses factors influencing banks' strategies to maintain their lending relationships and mitigate default risk.

Considering the concerns identified in the first essay, the second essay models banks as agents interacting through loans to tackle the system complexity. The model uses blockchain technology to improve the security of the system in a decentralized way. Indeed, this essay proposes an agent-oriented, blockchain-based design of the interbank market system, where the main objective is to decide on the times and methods of liquidity supply and demand by various market players based on what has been learned from the information available.

¹ Journal of Economic Literature

The third and fourth essays focus more on trust relationships between market players and simulate the effects of using a blockchain consensus algorithm in creating and maintaining banks' relationships and their impact on market stability. The results show that the use of blockchain to restore trust in the market helps increase financial stability by postponing the cascade of failures.

IMPACT STATEMENT

The model, findings, analysis, and insight presented in this dissertation can provide the following benefits to both researchers and practitioners in the fields of monetary policy and interbank market:

- An in-depth review of the literature of the recent century to provide a standard definition of the interbank money market and form a body of knowledge regarding the main concerns of this market and the factors affecting them
- A complete model of interbank market players' interactions with each other and with their environment, which uses the information from banks' balance sheets to simulate these interactions
- A blockchain-based consensus model for endorsing the trustworthiness of banks in the interbank market for lending decisions by other banks

Also, the following can be of interest to researchers and practitioners in the field of multi-agent systems:

- A conceptual design of blockchain integration with a multi-agent system
- An implementation of integrating an actual consortium blockchain with an agent-based simulation platform

STATEMENT OF CONTRIBUTIONS

The work presented in this thesis would not have been possible without the contributions of many brilliant people, to whom I am very grateful. Due to the collaborative and interdisciplinary nature of this project, many parts of the model developed and some of the analyses were acquired with the comments and guidance of my PhD supervisors. Also, this project has benefited from the suggestions and help of Dr. Önder Gürcan from the CEA LIST laboratory in designing the blockchain part of the model. By controlling the sequence of messages and drawing formal rules, as well as adding some content regarding blockchain, he contributed to the preparation of the UML models in Chapter 3. Also, Mr. Arthur Raimbert, who was assigned to the project to do his Master's internship, made some improvements in the performance of the model presented in Chapter 5, especially in terms of multithreading.

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ABBREVIATIONS

ABM	Agent-based modeling
BDI	Belief, desire, intention
CBDC	Central bank digital currency
IMM	Interbank money market
MAS	Multi-agent system
OMO	Open market operation
SALSA	Search, Appraisal, Synthesis, and Analysis

1 INTRODUCTION

A GENERAL INTRODUCTION AND BACKGROUND TO THE AREAS OF INTERBANK MONEY MARKET, BLOCKCHAIN, AND AGENT-BASED MODELING AND SIMULATION

Through presenting four articles, this dissertation attempts to introduce an elegant model of a specific financial market with a great impact on the economy, i.e. the interbank money market (IMM) – also known as the interbank call money market, interbank call loan market, interbank lending market, or interbank market. The main difference between this model and the traditional IMM models is that market players perform lending transactions among themselves on a blockchain platform, a technology that seems to be able to promote trust between players when necessary and thereby increase financial stability in the market. This agent-based model (ABM), including banks and the central bank, employs a stochastic approach as well as a calibration process to make the agents' behavior as close to reality as possible in IMM simulations. Before jumping to the core of the dissertation, this chapter provides an overview of this field and relevant literature, and after highlighting the importance of the topic, it explains the research design and the relationship among the chapters (i.e. articles or essays). The findings reported in each article, before being presented in a separate chapter, are introduced at the end of this chapter and form points of connection with other articles.

1.1 DEFINITION OF KEY CONCEPTS

1.1.1 Interbank Money Market

The IMM is an official country-level or international market where banks lend large sums of money to each other when they need liquidity mostly in a short period. Banks' deficits are mainly due to stochastic withdrawals by depositors, which create intermittent liquidity shocks (Bruche and Suarez 2010). For example, when a large number of depositors withdraw their money from a bank, the bank may run out of liquidity and be forced to make up for it by borrowing from other banks. In other words, a bank whose loans granted increase more than other banks will find that its deposits and thus its interbank liabilities settled in central bank money (CBM) will also increase more rapidly than the others. This CBM must be borrowed in the IMM. This loan can be unsecured (i.e. trust-based) or secured (i.e. collateral-based). In the case of secured loans, the central bank may also intervene in the market by buying or selling government bonds to expand or contract liquidity in the banking system (i.e. open market operations—OMO). In contrast, unsecured loans are usually granted for brief periods (e.g. one day), mainly based on the trusting relationship between the lender and the borrower and their previous loan history (Affinito 2012, Iori et al. 2015, Temizsoy et al. 2015, Kobayashi and Takaguchi 2018).

1.1.2 Blockchain

A blockchain is a distributed (i.e. shared), immutable ledger that facilitates the process of recording transactions and tracking assets, whether tangible (e.g. cash) or intangible (e.g. intellectual property), in a business network. Consensus in blockchain refers to the process of achieving agreement among network participants on the current state of the ledger. In a decentralized and distributed system like blockchain, there is no central authority to verify and validate transactions. Instead, consensus is achieved through an algorithm that enables all nodes in the network to agree on the current

state of the ledger, ensuring that all transactions are accurate, valid, and immutable. Consensus ensures that the blockchain network is secure, transparent, and resistant to fraudulent activities. Today, this technology has turned from a margin of public interest to a paradigm-changing technology (Patel et al. 2020).

There are at least four main types of blockchain networks: public, private, hybrid, and consortium. A public blockchain (e.g. Bitcoin and Ethereum) is completely non-restrictive and permissionless, where anyone with access to the Internet, by having a user identity, without needing prior authorization, can post a transaction or participate in verifying a transaction. In contrast, a blockchain network that operates on a closed network (e.g. inside an organization) or is controlled by a single entity is a private blockchain. A hybrid blockchain is a type of blockchain that combines features of both public and private blockchains. In a hybrid blockchain, certain aspects of the network are open and accessible to anyone, while other aspects are restricted to authorized participants. One of the benefits of using a hybrid blockchain is its low transaction cost, as it requires only a few nodes to verify transactions. This, in turn, leads to a faster consensus time for the network. The consortium blockchain is a private blockchain in which multiple organizational members collaborate on a decentralized network. It eliminates the risks of network control by a single entity. It is worth noting that in a consortium blockchain consensus procedures are controlled by preset nodes. In this dissertation, the latter is used in modeling a blockchain-based interbank market.

1.1.3 Agents-based Modeling

ABM entails the computer representation of a set of micro-entities (i.e. agents) that interact and change over time, and their interactions make a macro-system (Epstein and Axtell 1996, Grimm and Railsback 2012). Adapted from the notion of multi-agent systems (MAS), ABM generally consists of three elements (Macal and North 2014). The first element is a set of agents that composes the complex adaptive system. Each agent is characterized by specific attributes (e.g. size, role in the market, equity) and behaviors (e.g. lending, borrowing, defaulting). An agent may have different natures

(e.g. lender, borrower) and can be autonomous, purposeful, intelligent (i.e. capable of adapting and learning), heterogeneous, dynamic, with its internal states varying over time. The second element is a set of agents' relationships and interaction methods (also known as decision rules or conceptual model) that describe how agents interact with each other and with their environment, and how their internal states evolve. The third element is the agents' environment or topology (e.g. interbank network), which sometimes may not be considered in the construction of ABM. However, if the environment is taken into account, it can be passive or active with dynamic features and behavioral rules.

ABM is particularly useful and attractive when the system being modeled is complex, adaptive; it involves agents that are autonomous, heterogeneous, and intelligent; the environment is very important and not fixed; and dynamic interactions among agents or between agents and the environment are intermittently formed and dissipated, which adds to the complexity (Bonabeau 2002, Siebers et al. 2010). In short, ABM is a bottom-up approach that makes it possible to discover individual-level behaviors and causal mechanisms leading to macro-level aggregate emergent phenomena (McAlpine et al. 2020). To do this, a population, an environment, and patterns must be replicated in such a way that the model produces characteristics or results similar to those observed in the real world (Wilensky and Rand 2015). In order to study the interbank money market and investigate the effects of using blockchain in this market on trust and other market concerns, agent-based modeling is used as the main tool in this research for the following reasons:

- The behavior of each bank in the system is non-linear and can be characterized by thresholds and conditional rules (Nier et al. 2007, T. Xu et al. 2016b, Li et al. 2019). It is impossible or difficult to describe the discontinuity in individual behavior by traditional methods, e.g. mathematical modeling (Bonabeau 2002).

- Non-Markovian behavior and temporal correlations due to memory, dependence on the behavior of other banks, and hysteresis lead banks to adapt (Barroso et al. 2016, Liu et al. 2018).
- The interactions of banks are heterogeneous and can generate network effects known as systemic risk (Nier et al. 2007, Halaj 2018). Traditional methods generally assume global homogeneous mixing, but the interaction of banks in a network and the topology of this network can lead to significant deviations from the predicted aggregate behavior (Bonabeau 2002).
- Methods that use averages or tend to smooth fluctuations are ineffective for this study, because the banking system may be linearly stable but unstable to large shocks and perturbations (T. Xu et al. 2016b, Halaj 2018, Gaffeo et al. 2019).

1.2 BACKGROUND OF THE STUDY

An IMM, as a highly stochastic economic environment (Mitja Steinbacher and Jagrič 2020), is a complex adaptive system (Glass et al. 2011, Chiriță et al. 2022) where banks lend large amounts of money to each other at interbank rates when they need liquidity in a short period, thus adapting to this stochastic environment. The IMM plays a crucial role in the banking system, and more broadly, in the economic system by refinancing banks in liquidity, leading to financing the economy by the banking sector (Freixas and Jorge 2008a, Mistrulli 2011, Ben R. Craig et al. 2015). An IMM that freezes makes it impossible or too expensive to refinance banks (Allen et al. 2014, Bucher et al. 2019). In such a case, medium- and long-term financing for other businesses may immediately dry up. This situation quickly turns into a major recession and a rise in the unemployment rate (De Haas and Van Horen 2012, Acharya and Merrouche 2013). For instance, the subprime crisis of 2007 and the collapse of the Lehman Brothers in

September 2008 led to tangible dysfunctions in the market and a sharp deterioration in economic activity.

Banks' liquidity needs are continually evolving, and this makes a bank, which is the lender of liquidity today, the borrower of tomorrow. Managing the volatility of the interest rate due to the dynamicity in daily liquidity supply and demand are mostly devolved to central banks (Freixas and Rochet 2008). The importance of this issue is because instability in the market can lead to a higher risk of bank failures and contagion (Brock and Suarez 2000, Barroso et al. 2016) and even banking crises and the emergence of deep downturns (Gurgone et al. 2018, Popoyan et al. 2020). As displayed in Figure 1.1, market shocks caused by declines in the economy affect lending relationships and thus change market structure. In short, increasing demand for liquidity in the market raises interest rates (Taylor and Williams 2009), which, along with increasing client withdrawals, will weaken the situation of debtor banks. It is likely that some banks with excess liquidity refuse to lend for fear of their counterparts' insolvency and loss of their capital (Aldasoro et al. 2017, Serri et al. 2017). Other lenders may not consider previous lending relationships and charge higher premia for identical contracts or ask for high-liquid securities as collateral (Barroso et al. 2016), especially for riskier borrowers.

These difficulties in compensating for liquidity deficits may lead to the default of some debtor banks and ultimately their failure (Taylor and Williams 2009, Barroso et al. 2016). The failure of banks, on the one hand, destroys public confidence towards the banking system, increases withdrawals, and decreases liquidity in the market, and on the other hand, causes more fear in lending banks, leading to hoarding of liquidity by them and the occurrence of a liquidity crisis in the market (Heider et al. 2009, Acharya and Merrouche 2013, Gale and Yorulmazer 2013). All these are the promoters of intensifying the economic crisis. The financial crisis of 2007–2008 is an example to consider the interrelationships between liquidity and the ability of financial institutions to pay off debts and to prove the important role of the IMM in the economy (Adrian 2015). Although relationship lenders (i.e. banks that lent to peers based on their prior

relationships) played a key role as liquidity providers, they nevertheless forced borrowers to pay premiums for transactions (Liberati et al. 2015, Temizsoy et al. 2015).



Figure 1.1. The cycle of intensifying the financial crisis caused by the trust crisis and the liquidity crisis in the IMM. The figure shows the cycle of financial crisis intensification due to the combination of lack of liquidity and reduced confidence in the interbank market.

The results of the literature review in this field show that *contagion and systemic risk, stability, market structure, relationship and trust*, as well as *default and failure* are the most critical concerns affecting the decisions of market players in the supply and demand of liquidity in the IMM. The central bank seeks to reduce systemic risk and prevent financial contagion (Li et al. 2015, Barroso et al. 2016, Leventides et al. 2019), as well as managing the network (Acemoglu et al. 2015, León et al. 2018) in a way that makes the IMM more stable and resilient to shocks (Acemoglu et al. 2015, Hübsch and Walther 2017, Leventides et al. 2019). Furthermore, banks attempt to maintain their lending relationships (Fricke and Lux 2015, Kobayashi and Takaguchi 2018) and

reduce the risk of failure to meet the legal obligations (Li et al. 2015, Barroso et al. 2016).

One of the main challenges mentioned by many researchers in this field is the over-confidentiality of market information, especially information related to loan transactions, and the lack of easy access to this information. This makes it impossible for market actors to access their peers' information and estimate their degree of trustworthiness. Several researchers have addressed the positive effect of information availability in reducing systemic risk (Thurner and Poledna 2013, Barroso et al. 2016, Ding et al. 2017) and increasing trust (Affinito 2012, Anand et al. 2012, Marzo and Zagaglia 2014, Ben R. Craig et al. 2015) in the IMM. Since the advent of blockchain technology could provide facilities for the secure recording and sharing of market information (Lewis et al. 2017, Paech 2017), the simulation of an IMM benefiting from this technology^{2,3} is on the agenda in this dissertation.

Blockchain technology does provide some inherent security features 'out-of-the-box' due to its design and architecture. One of the primary security features of blockchain is its immutability. Once a block is added to the chain, it cannot be modified or deleted, which makes it nearly impossible to tamper with the data. Additionally, the decentralized nature of blockchain means that there is no single point of failure, reducing the risk of cyber-attacks and data breaches. However, it is important to note that the security of a blockchain system also depends on its implementation and the security practices of the users. Poorly designed or implemented blockchain systems can still be vulnerable to attacks, such as 51% attacks or smart contract vulnerabilities. Therefore, it is important to carefully design and implement blockchain systems with security in mind and to follow best practices for secure development and deployment.

² <https://www.bis.org/publ/work924.pdf>

³ <https://www.bis.org/about/bisih/topics/cbdc/helvetia.htm>

The main idea regarding the use of blockchain in the interbank market is that it should first keep the information of exposure between banks confidential for both ends of the relationship. Second, it should be able to provide the necessary information for banks to assess the risk of their counterparty and help them make decisions regarding lending to borrowing banks by providing this information to the nodes that need it in the network. As described earlier, consensus in blockchain refers to the agreement among the nodes in the network about the current state of the shared ledger. In the context of our study, consensus among banks on the level of trust demonstrated by a given bank, and comparing it with the expected trust of lending banks can be considered as a mechanism to decide about the loan state, whether to reject or register it in the system. This way, it helps to manage trust in the banking network by ensuring that all participating nodes agree on the validity of transactions and the state of the ledger.

To observe the effects of such external factors (e.g. adoption of blockchain technology) on IMM concerns (e.g. contagion or stability) that lack solid empirical evidence, scholars studying this market often resort to simulation methods to test how a set of exposures under different conditions will affect individual banks as well as the entire banking network (Upper 2011). The results of the investigation of the methods and approaches used in research in the field of IMM show that ABM for simulation is one of the three most popular methods among researchers in this field (see Figure 2.7). Using ABM, the network of interbank exposures and default events can be endogenously generated from behavioral rules followed by banking agents. This is the most important advantage of this approach compared to methods such as stress testing, which usually provide no more than a few snapshots of the banking system, even when detailed information on banks' bilateral exposures is available (Iori et al. 2015).

1.3 SIGNIFICANCE OF THE STUDY

1.3.1 Problem Definition

In an extensive financial market network, where each node represents several market operations, many entities interact non-linearly with each other, making it a complex system. Undoubtedly, IMM is one of the most complex systems in banking and monetary policy (Gai et al. 2011, Roukny et al. 2013, X. Gao et al. 2017). The multiplicity of actors with constantly changing roles from lender to borrower and vice versa, especially when the central bank intervenes in the market as a lender of last resort, along with the variety of lending methods, are the primary reasons for the complexity. The stochasticity of the overall demand for short-term liquidity and the likelihood of domino failures of tightly connected competitors in this environment are another source of complexity. A further aspect of the complexity comes from the different concerns of market participants and their influence on the goals and decisions of banks in the supply and demand of liquidity. The asymmetry of information available to different actors due to the difficulty of accessing information by smaller actors can be added to all these.

A way to reduce the complexity of a system with these specifications could be to use self-organizing ABM (Haber 2010). ABM provides a computational representation of a set of micro-entities (i.e. agents) interacting with each other and changing over time that form a macro-system (Epstein and Axtell 1996, Grimm and Railsback 2012). As a bottom-up approach, ABM makes it possible to discover individual behaviors and causal mechanisms that lead to macro-level phenomena (McAlpine et al. 2020). However, before designing and building an agent-based model of IMM, it is necessary to accurately identify the IMM environment, agents' behavior, and the factors affecting the decision-making and interaction of agents with each other and with their surrounding environment. It is worth mentioning that although the rules and procedures of interbank markets in different countries are similar in terms and generalities, in many cases they do not follow the same standard in details and are

dependent on the policies of central banks. Therefore, the lack of a single common reference is one of the research problems in this field.

Regarding solving the problem of information asymmetry, the use of blockchain technology is considered a potential solution (Yu et al. 2018). Due to the complexity of the IMM and the number of participants involved and the interactions among them, blockchain technology can help reduce information asymmetry by ensuring that all market participants have all the necessary information to make decisions about whether or not to lend to the applicant nodes. One of the challenges that this dissertation seeks to handle is to find a way for banks to reach a consensus in the blockchain on the level of trustworthiness of an applicant borrowing bank.

1.3.2 Research Gap

First, to the best of our knowledge, no concrete definition of the IMM can be found in the literature, as relevant research is mainly based on data available in particular countries, and each country typically has its own interbank market, which results in variations in structure and definition. Many scholars consider a number of influential factors as the concerns in the IMM (e.g. Furfine (2003), Martínez-Jaramillo et al. (2010), Angelini et al. (2011), Acharya and Merrouche (2013), Dičpinigaitienė and Novickytė (2018)) and several researchers survey various aspects of this market (e.g. Hasman (2013), Dičpinigaitienė and Novickytė (2018), Pozlep (2018)). However, it is believed that there is still a lack of a comprehensive study that identifies the roots of major concerns and integrate them into the body of knowledge of this field.

Second, in recent years, partial research has been conducted using agent-based simulation on systemic risk (e.g. Barroso et al. (2016), Gurgone et al. (2018), Halaj (2018), Calimani et al. (2019)), stability (e.g. Gurgone et al. (2018), Popoyan et al. (2020)), market structure (e.g. Georg (2013), Gurgone et al. (2018)), trust (e.g. Iori et al. (2015)), and default (e.g. Barroso et al. (2016), Smaga et al. (2018)) in the IMM.

However, it is rare to find a complete work using an agent-based model that covers all of these concerns to help decision making in the market.

Third, there are few studies on the application of blockchain in IMM. Guo and Liang (2016) mention a number of standardizations by various associations and countries regarding the use of blockchain in the IMM. Cucari et al. (2021) discuss a case study of the Spunta project in the Italian banking sector and argue how the project uses blockchain to create greater transparency and visibility, faster execution, and the ability to transfer checks and money directly within the banking network. Also, the number of studies in the field of agent-based systems that involve blockchain in their design and focus on common concerns with IMM such as trust are few. Calvaresi et al. (2018b), who implement a system to compute agents' reputations using smart contracts, and Khalid et al. (2021), who propose maintaining trust in an agent-based distributed energy market by publishing information on inter-agent agreements in the blockchain, can be counted among this category, but not in the context of IMM. There seems to be a gap regarding the use of blockchain in IMM considering the role that this technology will play in the future of the banking industry (Patel et al. 2020). An ABM that can help study the effects of using blockchain in IMM will make a meaningful contribution to filling this gap.

1.3.3 Contributions of the Study

Conducting a systematic literature review as the first step in writing this dissertation,

- aims to provide a comprehensive, complete definition of IMM that has not already been provided by researchers in this field.
- summarizes the available evidence on the specific concerns of actors and criteria they widely use in the selection of market strategies.
- identifies gaps in the existing research in order to suggest areas for future studies.

- provides a background allowing to position new research activities.

The second step in conducting this research, designing an agent-based system, contributes to the literature in the following three ways:

- providing an agent-based architecture that supports all the functions and concerns associated with liquidity supply and demand in the IMM.
- establishing a high-level mechanism for using learning agents in system design.
- considering the use of blockchain as part of the architecture of the target system.

The other two steps taken in this research contribute to the literature in at least two ways:

- adding to the literature on interbank trust.
- using blockchain (both actual and abstract) as part of the simulation platform.

1.4 RESEARCH DESIGN

This section discusses the overall strategy chosen to integrate the various components of the study in a coherent and logical way and ensures that the research problem is effectively addressed. In fact, it constitutes the blueprint for the collection, measurement, and analysis of data during this project.

1.4.1 Research Objectives

The outcomes aimed to be achieved by conducting this research are as follows. These objectives are revised and adjusted in subsequent iterations as the resolution of the project scope increases.

1. identifying the main factors affecting the market members' supply and demand decisions (theoretical objective)
2. integrating blockchain with the IMM in such a way that by balancing the identified factors, it improves the decisions of the actors and increases the efficiency of the market (theoretical objective)
- 2'. integrating blockchain with the IMM in such a way as to increase trust among the members and thus reduce the number of defaults and systemic risk and increase stability in the banking network (adjusted after achieving objective 1)
3. designing and implementing an ABM to simulate an IMM with the specifications mentioned above (empirical/experimental objective)

Therefore, the main goal of this dissertation is to develop an ABM platform to simulate the behavior of banks in an IMM benefiting from blockchain in which loan transactions are authorized by market members' endorsement. This dissertation will address the concerns identified in the literature review in the following ways. The platform developed in this dissertation simulates the behavior of banks over time based on the available data and evaluates the impact of applying and not applying a distributed *trust* system using blockchain on market *stability* during a series of simulations. In these simulations, the *default* of debtor banks is considered the primary source of *systemic risk*, because it reduces the assets of their creditor banks, releasing shocks in the market. Also, the difference in the shape of the *network* in two modes of using and not using blockchain is examined.

1.4.2 Research Paradigm and Theories

Scientific research philosophies are overall conceptual frameworks within which researchers work; that consists of a sets of beliefs and common agreements among scientists about how to understand and address problems (Kuhn 1970). Grounding a theory through appropriate paradigms and related assumptions is useful for researchers because it avoids the common tendency to force theory-building techniques into one single approach (Gioia and Pitre 1990). Therefore, this specific perspective is used in this study reflecting our assumptions and beliefs towards the subject.

Figure 1.2 outlines the research paradigm of the study. Besides the balance sheet operations of banks, which are used in compliance control and detection of liquidity surplus/deficiency, the use of blockchain can strengthen trust in the market. Together, these three (i.e. liquidity, compliance, and trust) form the basis of banks' decision-making for borrowing and lending in the IMM. The decision of the lending banks to lend to the borrowing banks or to reject their loan requests affects the survival or failure of the banks and consequently, the propagation of the cascade of failures in the banking network, the stability of the market, and the shape of the network. Also, if the loans granted are not repaid, they will signal negative feedback on the trust between the borrowing and lending banks.

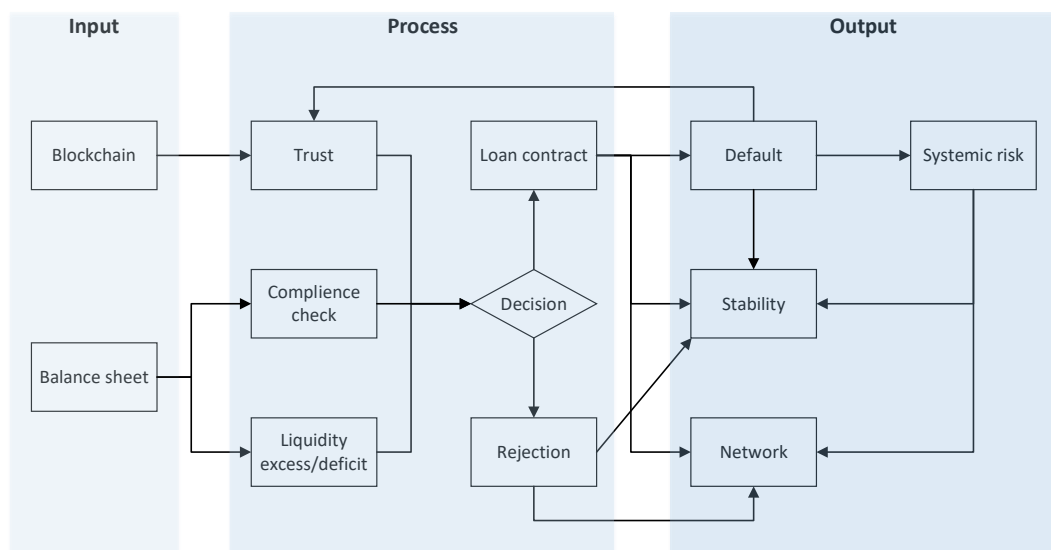


Figure 1.2. Research paradigm on how blockchain impacts IMM concerns. The figure outlines the input-process-output (IPO) model for the research paradigm of the study.

According to the economic theory of systemic risk, the presence of a negative externality of one bank's failure on the health of other banks causes the spread of default in the network, where the failure of banks with linked investments increases the risk to the entire economy (Rochet and Tirole 1996, De Bandt and Hartmann 2000, Acharya 2009, W. Silva et al. 2017). Also, with the notion that the relationship between two banks is established, continued, or interrupted based on the cost and benefits resulting from that relationship, the theory of social exchange is suited to understand the relationship between lending and borrowing banks. Unlike the economic exchange theory, the elements of social exchange are diverse and cannot be reduced to a single interest rate (Leichty 2005). The reason for choosing social exchanges for this study is that they focus more on trust than on legal obligations, are more flexible, and rarely involve explicit bargaining (Stafford and Kuiper 2021). Theoretical foundations for selecting these factors are given in Section 2 as well as the background section of the other three articles (see Sections 3.2, 4.2, and 5.2).

1.4.3 Research Questions

At first, the following two main questions were raised in the initial project proposal based on some of the literature reviewed earlier.

- Which learning methods and evolving forms of knowledge can help maintain trust between market players?
- Which market configurations and stakeholder strategies are more likely to stabilize the interbank market?

As the project progressed and we deepened into the subject, new research questions were raised in line with the previous two primary questions. In fact, increasing the domain resolution in the later stages is the main reason for the evolution

of the research questions, which the various essays included in this dissertation have been provided to answer. Table 1.1 addresses the evolution of these primary questions during the project and the chapter(s) of the dissertation devoted to answering the secondary questions. As shown in Table 1.1, the second article (Chapter 3) is considered to link the two primary questions, as it answers the secondary questions arising from them.

Table 1.1. Evolution of research questions. The evolution of research questions during the project is presented in the table.

#	Primary RQ	Secondary RQ	Chapter
1	Which learning methods and evolving forms of knowledge can help maintain trust between market players?	What are the main concerns of the IMM? What are the origins of each concern? How they affect concerns?	2
		How can agents store their knowledge and learn to reach better consensus on market transactions?	3
2	Which market configurations and liquidity supply/demand strategies are more likely to stabilize the market?	What design of the multi-agent approach can support all the IMM dynamics? How this design can benefit from blockchain to increase the stability in the market?	3
		What effect do different levels of uncertainty as a proxy for trust have on the banking system's stability in different economic situations? Can the use of blockchain help increasing trust among banks and stabilize the market in times of crisis?	4, 5

1.4.4 Research Approach and Method

To the best of our knowledge, the connection between IMM and blockchain has not been addressed before. Therefore, an exploratory approach using ABM (Kuhlmann 2021) has been taken to address the problems mentioned in Section 1.3.1 and to answer the research questions (Section 1.4.3). Many simulations using ABM can be found in the interbank market literature (see Sections 2–5). It is worth noting that research using this method regarding the use of blockchain in other fields such as the supply chain is emerging. However, since the integration of blockchain with IMM is a new topic, the purpose of this exploratory research is to discover possible relationships between variables, and hence, no prior assumptions or hypotheses are intended.

Figure 1.3 illustrates the processes that connect the banking system with relevant data, model development, and eventual output. As with any study, the argument can be made by collecting data from a variety of information sources (i.e. the Banque de France, the European Central Bank and the Federal Reserve). Model parameters are developed through an abstraction process. This model, designed for future use by academics or practitioners from central banks, aims to analyze the behavior of banks operating in the IMM when presented with a blockchain-based distributed trust mechanism, and to assess the effectiveness of this mechanism. Abstracts are compared with empirical data to assess their validity in a process called calibration. Calibration provides the basis for reliable model results. Finally, the output from the model simulation is tested through a process called validation.

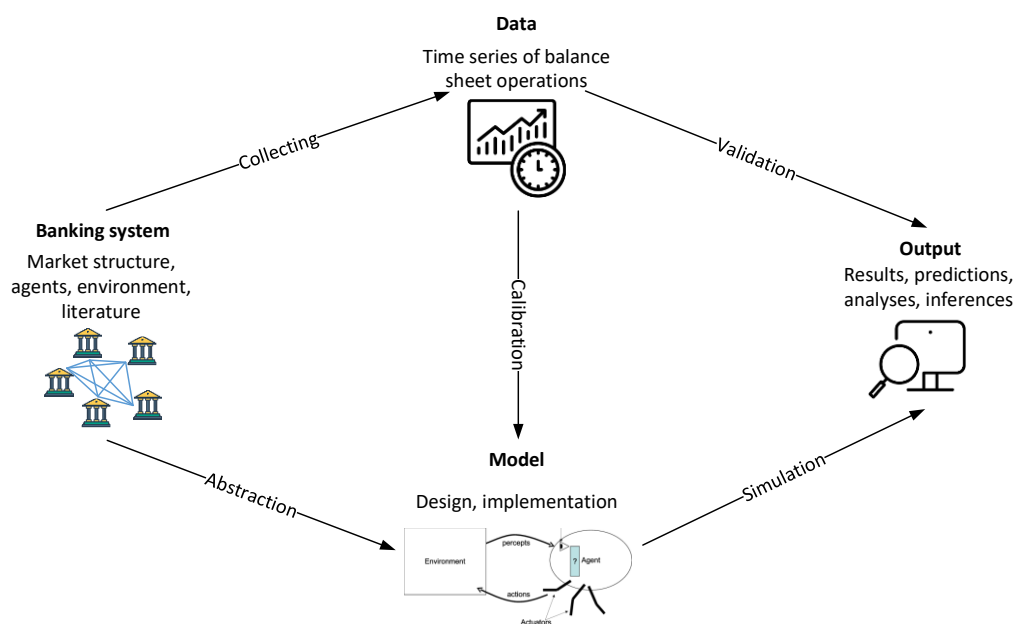


Figure 1.3. Research approach on how blockchain influences IMM. The figure displays the process of conducting the study, from concept to results showing the relationship between the banking system, model design, data sources, and model output. Key actions in the research process are indicated by directional arrows.

To support this approach, a four-step process based on Design Sprint method (Banfield et al. 2015, Keijzer-Broers and Reuver 2016) is considered as the overall research methodology. Design Sprint is a methodology proven as an iterative process to solve problems through designing, prototyping, and testing ideas. The iterative

approach allows the researcher to quickly create and test ideas and rapidly iterate on promising ones until they are shaped enough to be developed. The four main steps of the adopted methodology, which the four essays of this dissertation describe, are briefly as follows. In addition to shaping the overall project methodology, this iterative approach has been used in conducting each step of the project and completing the final products of that step. The details of each step are provided in Sections 2–5.

1. **Map:** This step maps out the problem and picks important areas to focus. This begins by performing a number of bibliometric analyzes on 609 publications in the field of IMM to identify the concerns of the market participants. Then, by reviewing in detail 160 publications focused on these concerns, the factors affecting them and the strategy of banks in facing each factor are identified. All these are performed to understand the various issues within the problem area, scrutinizing, synthesizing, and comparing relevant existing studies.
2. **Sketch & Decide:** This step sketches out competing solutions on diagrams to make decisions and turns ideas into testable hypotheses. This is manifested in the conceptual design of a multi-agent system for the interbank market that uses blockchain to record loan transactions between banks, and also suggests mechanisms for banks to reach blockchain consensus and learn from past behaviors. A set of UML diagrams is used for design in this step.
3. **Prototype:** This builds a realistic prototype of the system based on the previous design decisions. Aiming to create a ‘Goldilocks quality’ prototype, ideally, it should be good enough to look as real as possible, but not so great that it takes a lot of time to build. The IMM prototype rapidly integrates an ABM platform with an actual blockchain, quickly builds a model of agents interacting together, implements a minimal consensus algorithm on the blockchain, and conducts experiments with a small number of agents to explore their lending relationships.

4. **Test:** Using the feedback received from the prototype test, this step completes the model with the aim of maximally supporting the functional requirements and makes the necessary changes in the architecture and code of the simulation platform to support the non-functional requirements. Functional requirements to be supported in this step include the completion of market rules and the consensus method. Non-functional requirements are mainly focused on the performance of the platform by overcoming hardware resource limitations and parallelization of processes. Finally, the previous scenarios are tested again on the new version of the platform and the results are analyzed.

1.5 ORGANIZATION OF THE DISSERTATION

This section introduces the structure and main contents of this thesis, which are presented in the form of four essays. The purpose of each chapter and the expected deliverables and outcomes are identified in Table 1.2.

Table 1.2. Purpose and outcome of dissertation sections. The table introduces the different chapters of the dissertation, including the purpose of each chapter and its expected deliverables and outcomes.

Chapter	Purpose	Outcome
1. Introduction	Present essential components of research and describe the initial layout	Research problem, research objectives, research questions, research significance, and main concepts
2. MAP: Literature Review	Review background and analyze relevant literature to establish solid groundwork	Literature review on IMM network, stability, systemic risk, default, and trust Bibliometric analysis
3. Sketch & Decide: An Architectural Design	Design an IMM future MAS that covers all the concerns of market players using blockchain	Design model, UML diagrams, important scenarios

4. Prototype: A Minimal Model	Present details of construction of ABM and explicitly establish rules for computer implementation Outline experimental setup, present analyses and results	Specific research method and steps of the ABM to be used for simulation Results of simulation, general and specific canons of research
5. Test: A Maximal Model	Improve the model of Chapter 4 and make it closer to reality	Data interpolation, model calibration Results of simulation, general and specific canons of research
6. Conclusion	Establish closing arguments, discuss important aspects in addition to the main section	Limitations, delimitations, contributions and future research
7. Résumé en Français	Provide a French synopsis of the four essays	Research questions, methodologies, models, findings, contributions, limitations, and future work of four essays in French

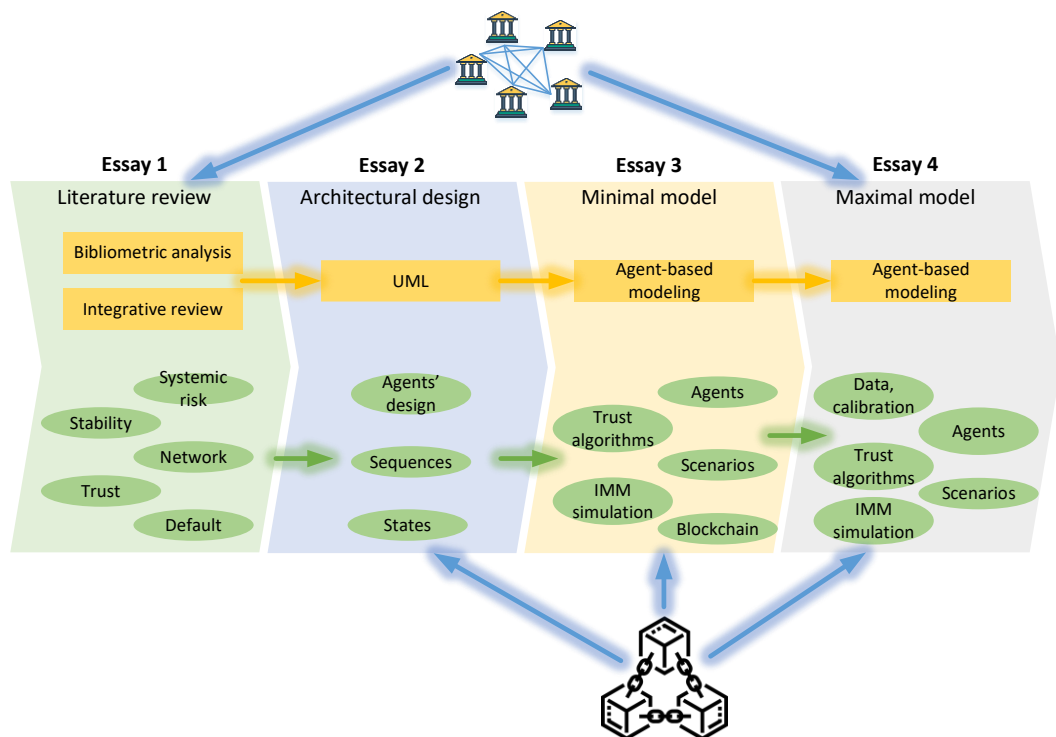


Figure 1.4. Content map of the dissertation. The figure shows the structure of the dissertation and the relationships among different essays and content.

Also, Figure 1.4 shows the main structure of the dissertation in the form of a map explaining the relationships among different essays and content (chapters 2–5). It

presents each essay sequentially by outlining the basic rationale of the underlying study, the research questions, and the methods used, as well as highlighting the results. In the naming of the essays, in addition to mentioning the title of the article, an abstract title based on the steps of the Design Sprint method is also used. This name attributes the nature of each essay and the efforts made for it to a phase in Design Sprint that has always been considered during the implementation of each step of this research.

1.5.1 Map: A Literature Review

The first essay raises the question of what are the main concerns of the actors of the interbank money market and the factors affecting these concerns, and how the set of these factors shapes the strategies of the actors. Today, after several banking crises in the last two decades, there is considerable literature on the factors influencing the decisions of liquidity supply and demand by banks and the central bank in the interbank market. However, regarding some factors, no consensus has been reached among scholars on whether these effects are positive or negative on criteria such as market stability and structure. It is argued that this lack of agreement is due to the lack of a solid theoretical framework in this field that addresses in detail all the concerns and factors affecting them. By conducting a scientometric analysis and a systematic review of the recent literature, this essay redefines the IMM and provides a model of the criteria influencing the IMM actors' decisions.

The related research mainly expresses the established view in some countries to the notion of IMM based on the data accessible in those countries. Because each country usually has its own IMM, different structures and definitions are observed. Therefore, this essay begins by providing a unifying definition of the IMM. It is defined as:

“an official country-level or international market where banks lend large sums of money to each other when they need liquidity mostly in a short period.”

This definition comprehensively refers to all the researched aspects of the interbank market. It refers to (i) the formality of the market and being controlled by a regulatory entity; (ii) its geographical distribution, whether domestic or international; (iii) the main tradable thing in the market, i.e. liquidity; (iv) the main processes of the market, i.e. lending and borrowing; and (v) the short-term nature of the market. This definition provides me with a criterion for deciding whether to include or exclude the searched documents in the review process at a later stage.

After stating the problem and the importance of conducting research, this essay uses an iterative approach in implementing a systematic review methodology formulated based on SALSA (Grant and Booth 2009). First, by performing bibliometric analysis of keywords and text mining in the title and abstract of 609 publications, five concepts are identified as the main concerns of actors in IMM. These concerns are ‘contagion and systemic risk,’ ‘stability,’ ‘market structure,’ ‘relationship and trust,’ and ‘default and failure.’ Contagion and systemic risk refer to the interdependence of banks, and transmission of risks across the whole of the market. The meaning of stability is the state in which the IMM is resistant to economic shocks and is fit to smoothly fulfil its basic operations to address the worries about volatility in prices and rates in the market and have a stable environment for the operations of money supply and demand. The market structure includes all topics related to network topology and market configuration, while relationship and trust are connected with the history of all fiduciary relationships between market players. Finally, default and failure mean the failure to meet the legal obligations of a loan.

A detailed review of 160 studies related to the aforementioned five concerns results in a framework for research in this field containing the factors influencing the concerns and how they are affected. Figure 1.5 briefly shows this framework, which is described in detail in Tables 2.6 to 2.10. As shown in Figure 1.5, besides the characteristics of the banking network (i.e. market structure), which includes a wide range of factors, the characteristics of banks, including their size, are the most influential factors on the decision-making criteria of banks in the market. Meeting regulatory requirements regarding capital and liquidity, along with interest rates and

market shocks, are the next important factors that, according to the literature, have significant effects on the five concerns of the market.

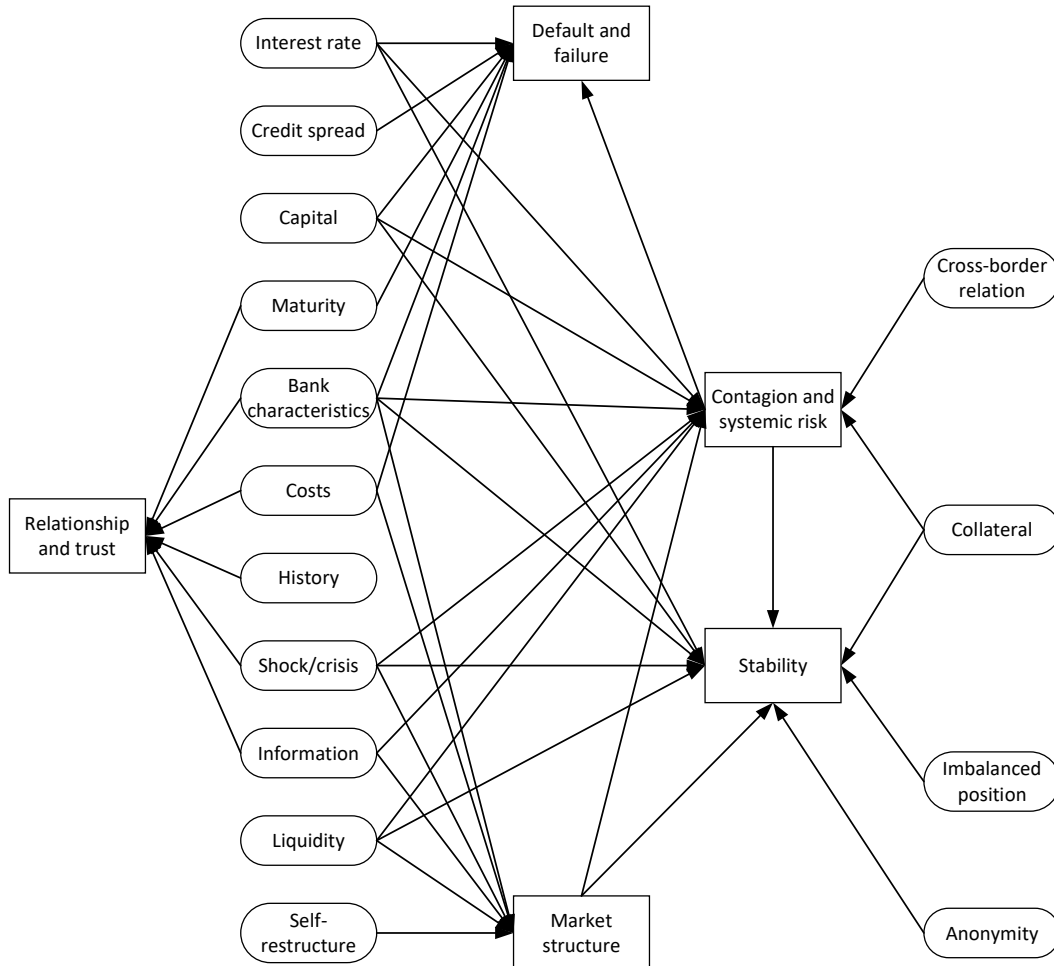


Figure 1.5. Factors affecting IMM concerns. The figure displays a framework for research in the field of IMM containing the main concerns and factors influencing them.

The results of text mining of suggested extension points in the reviewed publications help to identify trends and directions for future research on IMM concerns. Accordingly, by listing a set of commonly used themes in this regard and presenting a picture of the historical evolution of these themes, this essay presents a number of propositions as future avenues for researchers in this field. The nine main themes that have been of interest to scholars in the literature since 2013 are stability, default, network structure, balance sheet, central bank, liquidity, contagion, dynamics, and capital. The essay concludes with a list of limitations and implications, as well as a

number of new agendas for the future related to the findings. The most important ones that are related to the topic of this dissertation are the study of mechanisms for symmetrical sharing of information among market members in a way that helps to improve their decisions and increase trust in the market as well as the use of artificial intelligence in the models developed for predicting market members' behaviors.

1.5.2 Sketch & Decide: An Architectural Design

Aiming to support the market concerns identified in the first essay, the second essay seeks to discover the answers to these two questions: (i) What multi-agent architecture can support all the IMM dynamics, and how can this architecture benefit from blockchain to increase the stability in the market? (ii) in such an architecture, how can agents store their knowledge and learn to reach a better consensus on market transactions? Although there is no clear answer to these questions in the literature on the interbank market, this essay attempts to propose a new architectural design for this purpose with the insight gained from the literature on the fields of multi-agent systems and blockchain and their integration with the specific requirements of the IMM.

This essay presents a design of a multi-agent architecture for the interbank market where interbank loan transactions are stored on the blockchain to reduce information asymmetry and increase market stability, especially in times of crisis. As shown in Figure 1.6, this architecture is able to simplify the complex tangle of different market routines caused by the multiplicity of actors and different types of loans by replacing the roles and systems with a number of holonic⁴ agents (compare it with Figure 3.1).

The proposed architecture consists of three main zones: the borrower bank, the lender bank and the central bank. In general, one agent in each zone is considered responsible for collecting data from the bank's internal or external systems. Another

⁴ Agent groups consisting of coalesced agents

agent is responsible for planning the receipt or payment of loans. The responsibility of negotiating with the agents of other banks based on previous learnings and concluding a loan agreement is also the responsibility of another agent in each zone.

The borrower bank holon is comprised of the three agents responsible for data collection, planning and trading, associated with a set of internal systems and interfaces to communicate with other agents. For example, calculating the liquidity deficit and setting borrowing targets are the responsibilities of the *LoanPlanner* agent, while the *Trader* agent sends the loan application to the other banks, receives the auction notice of the central bank, and finally concludes the loan contract. Also, in order to succeed in its negotiations with other agents, it must maintain its own sets of beliefs, desires, and intentions (BDI) (Braubach et al. 2004) along with learning methods. An instance of blockchain is considered in the architectural zone of this agent. It is assumed that the agent *Trader* is responsible for registering the final loan agreement on the blockchain in the form of a smart contract. Assigning a unique ID to a transaction, placing it in a block, and associating it with the previous block are all the responsibilities of the *Blockchain* in this design.

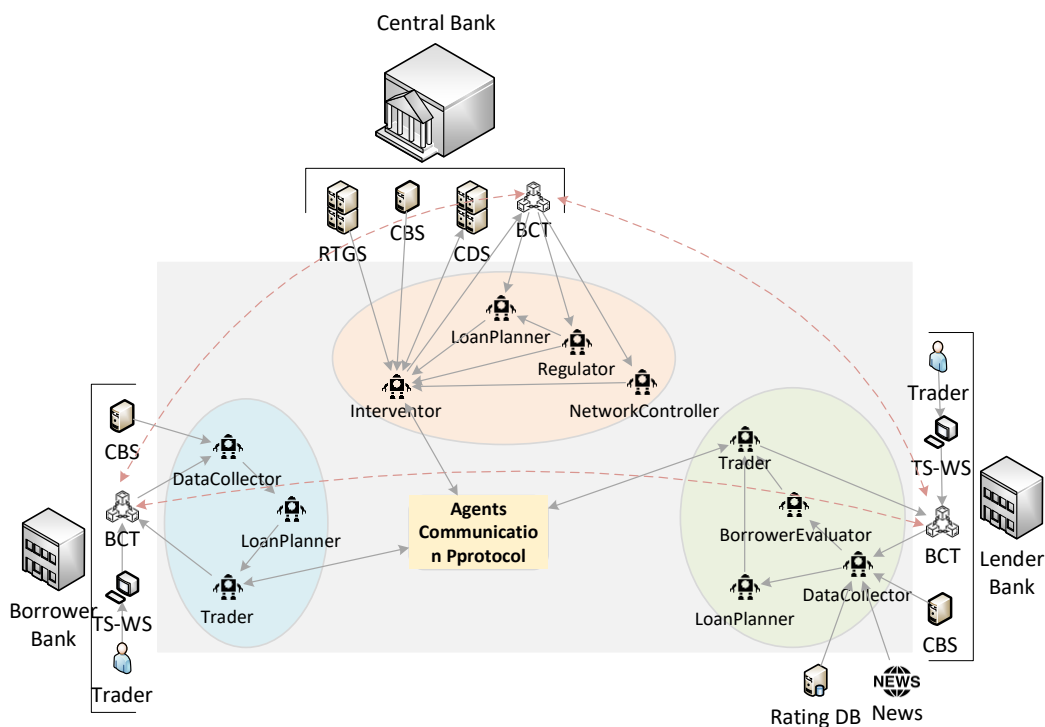


Figure 1.6. An Agent-oriented, Blockchain-based Design of the IMM. The figure demonstrates holons and their relevant agents designed for an agent-oriented, blockchain-based solution supporting IMM dynamics.

In the lender zone, *DataCollector* agent is responsible for reviewing the news and ratings of other banks from news sites and scoring systems so that it can later be used in risk calculations of banks that apply for loans. In this zone, the new agent *BorrowerEvaluator* is responsible for assessing the risks and the trust of the other parties to be considered in the proposed interest rate of loans. The structure and function of the other agents in this zone are similar to those of the borrower zone.

The nature and function of the agents of the central bank zone are also considered specific to the activities of this bank. The *Interventor* agent in this zone corresponds to the *Trader* agents in the other zones. Also, it has a number of additional tasks, for example, auctioning, blocking banks' securities as their collateral, clearing and settlement of transactions, etc. in this holon, the *Regulator* agent is responsible for dictating key market policies, and the *MarketController* agent is responsible for assessing market risks and identifying the factors that lead to market instability.

In the proposed architecture, consensus among network members is the most important feature provided by blockchain. To meet the requirements of our design, we looked to Corda technology due to its successful implementation in the Italian banking system. Corda uses a unique consensus mechanism called 'notary' that offers a form of transaction validation known as 'transaction finality'. This means that participants agree on the state of the ledger by reaching consensus on a set of transaction dependencies, rather than by having a majority of the network validate every transaction. This makes Corda more scalable than other blockchain platforms, while still maintaining a high degree of security and privacy. The notary consensus model consists of two steps. First, in a validity consensus model, each node verifies that transactions are valid and conform to the agreed-upon rules before adding them to the ledger. This consensus mechanism ensures that all transactions added to the ledger are valid, but it does not guarantee that all nodes in the network will agree on the final state of the ledger. Second, in a uniqueness consensus model, the focus is on

preventing the double-spending of digital assets by ensuring that each asset is unique and can only be owned by one party at a time. The uniqueness consensus mechanism guarantees that all nodes in the network will agree on the final state of the ledger.

It is assumed that *Trader* agents from banks not directly involved in a transaction, but with prior lending relationships with the parties, can act as endorsers to validate the transaction's validity. They use their common lending history with the parties to perform the endorsement. If the notary does not reach a consensus on the trust level (i.e. the endorsed trust level does not meet the expected trust level), the transaction will not be registered on the ledger.

Here is an example for learning agents to create a better consensus on the validation of transactions. Assume that endorsers are from different importance levels. Trust relationships will be especially helpful in gaining recommendations from higher-level endorsers. One of the goals of agents' intelligence in the proposed system is to enable them to intelligently identify their current alternatives, plan their actions, and respond to results to build trust by finding appropriate endorsing partners. According to the BDI architecture, one part of each agent's beliefs may include a copy of the blockchain containing data of the transactions to which the agent has access. These beliefs can be right or wrong and change over time as the market operates. Also, accepting or refusing other agents' endorsement can be seen as a desire that is updated as beliefs change. Once a set of possible actions is identified, the agent calculates and analyzes the reward, cost, priority, etc. to prepare an action plan. The output of the actions is evaluated, and the agent's intentions are updated accordingly. This is how agent intelligence is defined in the system.

After presenting two sequence diagrams for two example scenarios in the IMM, the essay concludes with a list of limitations and future work. The biggest limitation of this research is that it remains at the design level and lacks implementation and testing with real data at the time of publishing the article. Therefore, one of the future tasks could include building a prototype of the system. Simulating this system with an agent-based platform is another line of research addressed in the following essays.

1.5.3 Prototype: A Minimal Model

After identifying the criteria influencing the decision-making of interbank market players (the first essay) and designing a high-level architecture for an agent-based system integrated with blockchain to support the mentioned criteria (the second essay), the third essay attempts to implement and test a prototype of a significant part of this architecture. The main question of interest in this part of the research is how, and to what extent, the use of blockchain can help increase trust between banks and market stability in times of crisis, that is, when trust decreases.

To answer this question, a blockchain consensus algorithm is designed to increase trustworthiness in the market through the endorsement of banks applying for loans. This study combines the two values of the trust threshold ($\tau_{i,t}$) of the lending bank and the actual trust level ($\theta_{i,j,t}$) of the borrowing bank endorsed by the nodes of the blockchain network for the decision of banks in lending. The trust threshold of each bank is calculated based on its interaction with the central bank, equity, and size. The level of real trust between two banks at any time is calculated based on the previous relationship between them, if two banks already have a loan relationship; otherwise, it is calculated based on the endorsement of other banks with which they already had a loan relationship. A lending relationship between lender i and borrower j is allowed at time t if $\theta_{i,j,t} + \tau_{i,t} > 4$. This is the only rule based on which banks make their lending decisions in this model.

Also, ABM is used as a method to investigate the behavior of different banks in the face of this proposed technology. The simulation platform developed for this research involves a simple loan application developed on Corda – a consortium blockchain for financial services (Mohanty 2019), which is integrated with Repast Symphony (North et al. 2013) for the development of the IMM agent-based model and the simulator. All codes is developed in the Java language both in Corda and Repast. In this model, different levels of uncertainty caused by different economic situations are considered trust proxies.

Consortium blockchains, including Corda, store information in a distributed manner across the nodes participating in the network. In Corda, each node maintains a copy of the ledger, which contains a record of all the transactions that have been validated and agreed upon by the network. Each node also has access to a unique vault, which contains the states of the contracts that the node is involved in. The vault is used to store the current state of the contracts, as well as the historical data related to the contracts. This helps ensure that data is available and accessible to all parties involved in a transaction, while also maintaining data privacy and confidentiality. This is achieved through the use of several mechanisms designed to ensure data privacy and confidentiality. In Corda, each node has a unique public key and private key pair, which is used to sign and verify transactions. When a transaction is initiated between two parties, their public keys are used to create a shared symmetric key, which is used to encrypt the transaction data. The transaction data is only visible to the parties involved in the transaction, and cannot be accessed by other nodes on the network. In addition to the use of public-key cryptography, Corda also supports the use of confidential identities, which allow parties to transact on the network without revealing their actual identity. This helps ensure data privacy and confidentiality by preventing third parties from being able to link specific transactions to specific individuals. These features are in line with previous studies, such as Mancini et al. (2016), which highlight the crucial role of anonymity in the functioning of the IMM.

Figure 1.7 displays the UML deployment diagram of the prototype system. As shown in this figure, the agent-based simulator communicates with the loan system through an API developed in the project. The initiation stage in the model deploys one node of blockchain (i.e. Corda) for each agent. The deployed blockchain nodes containing the REST API that records loan transactions on the blockchain are then run at this stage. Therefore, the environment implemented to simulate agents' behavior is as similar as possible to the real environment that banks may use in an actual IMM by employing a real blockchain to record their loan transactions.

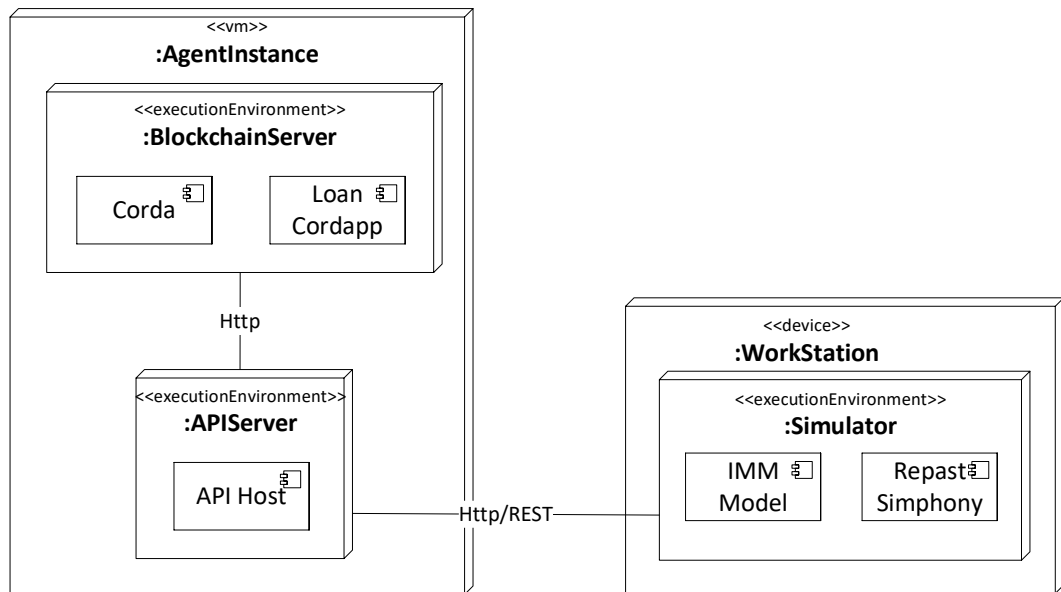


Figure 1.7. The UML deployment diagram of the prototype system. The figure shows the model of the physical deployment of software components used in the simulation platform on physical and virtual nodes.

Of course, this form of implementation (i.e. as similar as possible to the real environment) has its limitations. The main one is the computing power of the hardware, which limits the interbank market simulated in this research to a network with 30 banks. This simulation is done with 30 banking agents who are randomly selected from among 413 active banks in the French interbank market in small, medium, and large sizes and in compliance with the concentration of the French IMM. These banks communicate with each other by sharing a part of their balance sheet (i.e. interbank loans and debts). In this model, all interbank loans are considered unsecured, overnight. Also, in this model, the central bank agent (i.e. Banque de France), in addition to centrally clearing payments and matching liquidity in the market, regulates the market and helps banks avoid failure when necessary.

This essay first presents the simulation results of testing three scenarios for different economic cycles in the absence of blockchain (off-chain mode) and then tests the same scenarios in the mode where the proposed blockchain consensus algorithm is used for endorsing the level of trust between banks (on-chain mode). The average results of 10 simulations of each scenario for 350 days of banks' activity in IMM reveal

the same stability of banks in both the off-chain and on-chain modes under economic growth. However, with the decrease in economic growth and entering the crisis, the use of such a mechanism can postpone the cascade of bank failures for a significant period. Moreover, the results show that when blockchain is used in an unstable economic situation, both lending and borrowing banks prefer to reduce the number of contracts and increase the amount instead (i.e. trustworthy relationships).

The lack of access to actual data on interbank exposure is another limitation of this research. This can be partially overcome by interpolation and disaggregation of the quarterly aggregate data of banks' balance sheets and converting them into daily data in subsequent research, although it will not be considered the real data of banks. The development of a model that can cover more banks in the simulation and is as close as possible to the conditions of a real banking network is another thing that should be considered in future research. Using an interest rate corridor system, adding secured loans, and involving machine learning in simulating the behavior of banks based on past data are other topics that can be considered in future research.

1.5.4 Test: A Maximal Model

With the aim of expanding and generalizing the model presented in the third essay and its findings as well as overcoming some limitations mentioned regarding that model, especially the number of agents participating in the experiments, the fourth essay attempts to answer two questions: (i) What effect do different levels of uncertainty, as a proxy for trust, have on the banking system's stability in different economic situations? (ii) Can the use of blockchain to increase market confidence increase stability in times of diminished trust?

After reviewing the literature describing the role of trust in IMM and materials about distributed trust using blockchain, this research seeks to improve the logic of the model. Also, the simple equation for calculating the level of trust is enriched by involving two new variables of competitiveness and interest income as well as using

ordinal logistic regression. Moreover, a static interest rate corridor system is used, whose lower and upper limits can be defined as experiment parameters.

In order to overcome the limitation caused by hardware resources so that more agents can be involved in the simulation, the blockchain Corda gives way to an abstraction of a network among banks implemented by JGraphT. In order to establish the consensus-based decision rule mentioned in the third article, in the fourth essay, all the functionality related to the endorsement of the trust level of the borrowing banks is developed and simulated using the interfaces of the library JGraphT.

The paper studies the IMM dynamics in a situation where banks are required to enforce Basel III rules for interbank liquidity management consistently. As in the third essay, here the article simulates the market within three typical economic cycles and then adds a blockchain-based trust mechanism to each cycle and simulates the IMM again. Random values of noise and drift that are created by using uniform distributions in different economic conditions are applied in the production of daily balance sheet data of banks. Other simulation parameters are extracted from the Basel III framework and interbank market literature.

The average results obtained from 10 tests of each scenario with 413 banking agents confirm the results reported in the third article more strongly. It can be inferred from the longer delay time of failures in the new experiments compared to what has been reported in the third essay that the more the number of nodes in the network and, as a result, the number of connections of nodes to their counterparts, the more resilient the network. The results confirm the previous findings that in the off-chain mode, the general tendency of the borrowing banks is to borrow from more partners, and most of the lending banks tend to diversify their interbank loan portfolio and lend to more banks (i.e. extensive margin). By the intervention of the use of blockchain in the model, both parties prefer to reduce the number of agreements and increase the amount instead (i.e. intensive margin), which can be considered a sign of more trustworthy relationships.

The biggest limitation of this research, as before, is the lack of access to real data from the details of bank interactions, which makes it impossible to calibrate the model. Therefore, in this research, this calibration is nothing more than checking the model with quarterly aggregate data. Regarding future avenues, adding a dynamic corridor system to the platform that also covers negative interest rates, in addition to the ability to pay interest on banks' reserves, could be considered. The funds exchanged on this platform are now all overnight. Also, adding secured loans and repo⁵ to the model can make it more helpful in simulating real-world events in the future. Moreover, in this model, banks' decisions about lending, investing in securities, etc., have a stochastic basis like other events that take place outside their control. Another direction of research in the future can be the use of supervised learning and developing learning agents who make decisions based on their current and future goals and using what they learn from the past.

⁵ Repurchase agreement

2 MAP: A LITERATURE REVIEW

INTERBANK MONEY MARKET CONCERNS AND ACTORS' STRATEGIES – A SYSTEMATIC REVIEW OF 21ST CENTURY LITERATURE⁶

Abstract. As the reallocator of liquidity from banks with excess to banks with a deficit, the interbank money market plays a fundamental role in the proper functioning of the banking system and the economy as a whole. The aggregate uncertainty derived from stochasticity of the overall level of the demand for short-term liquidity and the likelihood of domino failures of tightly connected competitors who lend themselves vast amounts of liquidity explain the complexity of decisions in this environment. To identify the most significant factors influencing actors' strategies, first the five underlying patterns discovered through a bibliometric analysis of 609 scientific documents in this field are present: contagion and systemic risk, stability, market structure, relationship and trust, and default and failure. Then, our detailed study findings on 160 recent works indicate elements that affect central banks' strategies in reducing systemic risk and preventing financial contagion, as well as managing the interbank network in a way that makes it more stable and resilient to shocks to conserve market confidence. Furthermore, they address factors that influence banks'

⁶ This paper has been published by the Journal of Economic Surveys. Reference as: Alaeddini, M., Madiès, P., Reaidy, P. J., & Dugdale, J. (2022). Interbank money market concerns and actors' strategies—A systematic review of 21st century literature. *Journal of Economic Surveys*.

strategies to maintain their lending relationships and mitigate default risk. In addition to summarizing potential research directions, this paper provides market participants with a strategy fact-sheet.

Keywords. Contagion and Systemic Risk; Stability; Market Structure; Relationship and Trust; Default and Failure; Integrative Review

2.1 INTRODUCTION

Banks play a unique role in the modern economy by issuing claims that work as money, facilitating payments across economic agents, increasing the monetary base through credit creation, holding fractional reserves, and lending to each other. Ongoing banking activities include cash and accrual processes that take place within and across banks. Banks keep money in deposits on behalf of other agents, but their activity is mostly characterized by the capacity to use these deposits, especially for financial investments. This capacity involves money creation, coming from the bank-lending process. There is a two-way relationship between deposits and loans. Credits are granted thanks to existing deposits, but credits also create deposits. Banks put the credit created through a loan to a client into the client's demand deposit account. As soon as the client withdraws an amount from the account, either in cash or through the interbank payment mechanism, the money enters the economic cycle. Of course, the money generated will gradually disappear with the repayment of the loan. In this way, all banks are interdependent on the flow of payments, generating the 'banking system.' Because banks are structurally unbalanced due to money creation, interbank coordination is needed to maintain the banking system in operation (Biondi 2018), realized by central bank interventions, clearinghouses, and the interbank money market (IMM).

Unfortunately, no concrete definition of the IMM can be found in the literature, as relevant research is mainly based on data available in particular countries, and each country typically has its own interbank market, which results in variations in structure

and definition. In order to give readers a better sense as to the bounds of the survey and to know what markets and features we consider in the IMM, we provide the following definition of the IMM based on our findings from a review of a wealth of documents as well as our previous experiences. We consider the IMM to be an official country-level or international market where banks lend large sums of money to each other when they need liquidity mostly in a short period. Banks' deficits are mainly due to stochastic withdrawals by depositors, which create intermittent liquidity shocks (Bruche and Suarez 2010). For example, when a large number of depositors withdraw their money from a bank, the bank may run out of liquidity and be forced to make up for it by borrowing from other banks. This loan can be unsecured (i.e. creditworthiness-based) or secured (i.e. collateral-based). In the case of secured loans, the central bank may also intervene in the market by buying or selling government bonds to expand or contract liquidity in the banking system. The scope of IMM in this study includes the definition and functions mentioned and does not include other types of money markets or interbank markets (see Section 2.2.1).

Undoubtedly, the IMM, as a short-term provider of financial resources, plays a unique, crucial role in the banking system, and more broadly, in the economic system (Freixas and Jorge 2008a, Ismath Bacha 2008, Gertler and Kiyotaki 2010, Mistrulli 2011, Ben R. Craig et al. 2015). Indeed, it refinances banks in liquidity, i.e. central bank money (Faure 2012, Ryan-Collins et al. 2012, McLeay et al. 2014a, 2014b), leading to financing the economy by the banking sector. The singularity of this market comes from the fact that banks are competing entities who lend each other vast amounts of short-term liquidity, a situation not observed in other economic sectors (Chorafas 2003, Acharya and Merrouche 2013). This explains the influential interdependence of banks in the market as the transmission belt of risk and failure (Schnabl 2012, Allen et al. 2014, Caccavaio et al. 2015, Montagna and Lux 2017, R. Lu et al. 2018) and as a critical diffusion channel for financial distress during the crisis (Serri et al. 2017). An IMM that freezes or even becomes inoperative makes it impossible or too expensive to refinance banks (Allen et al. 2014, Bucher et al. 2019). In such a case, medium- and long-term financing for other businesses may immediately dry up. This situation quickly turns into a major recession and a rise in the unemployment rate (De Haas and

Van Horen 2012, Acharya and Merrouche 2013). For instance, the subprime crisis of 2007 and the collapse of the Lehman Brothers in September 2008 led to tangible dysfunctions in the market and a sharp deterioration in economic activity. These experiences explain why the banking sector is the most regulated economic sector and why central banks control banking liquidity as part of their monetary policy, to the point that sometimes they act as the ‘lender of last resort.’

The IMM is evolving in a complex and changing environment (Tirado 2012, Delpini et al. 2013). Banks’ liquidity needs are continually evolving, and this makes a bank, which is the lender of liquidity today, the borrower of tomorrow that reflects an extreme interdependence of banks. This variability in daily liquidity supply and demand is reflected in the volatility of the market rate (Whitesell 2006, Morten L Bech and Malkhozov 2016, Garcia-de-Andoain et al. 2016). Managing the dynamicity of demands and controlling the rates are socially useful objectives, mostly devolved to central banks (Freixas and Rochet 2008) because instability in the market can lead to a higher risk of bank failures and contagion (Brock and Suarez 2000, Dietrich et al. 2015, Barroso et al. 2016) and even banking crises and the emergence of deep downturns (Gurgone et al. 2018, Popoyan et al. 2020). Such unexpected events can cause market-based transparency indicators to be biased due to the volatility of the output gap and the inflation gap affected by unexpected news concerning production and inflation, as observed in the events of the high volatility of the Fed funds rate in late December 1985, the Russian debt crisis that led to the collapse of long-term capital management in 1998, and the financial crisis that began in the third quarter of 2007 (Papadamou and Arvanitis 2015), and, consequently, less confidence in the market (Bini Smaghi 2008). Loss of trust in the market leads to further domino failures (Li 2011) and increase in instability (Lux 2015), with many effects on market configurations (Fricke 2012, Finger et al. 2013). Making the best decision in such a complex and highly confusing environment requires, first and foremost, understanding the concerns of all participants and factors influencing those concerns so that, in the future, researchers can come up with a model for decision-making that supports the most relevant concerns of all market participants.

Many scholars have considered a number of issues, along with several influential factors as the concerns in the IMM (Bernard and Bisignano 2000, Furfine 2003, Martínez-Jaramillo et al. 2010, Angelini et al. 2011, Acharya and Merrouche 2013, Dičpinigaitienė and Novickytė 2018). Although several researchers have already surveyed various aspects of this market (Arman 2013, Hasman 2013, Caccioli et al. 2017, Dičpinigaitienė and Novickytė 2018, Pozlep 2018), to the best of our knowledge, there is still a lack of a comprehensive study that identifies the roots of major concerns and integrate them into the body of knowledge of this field. To answer the question that on what basis various market players make their liquidity supply/demand decisions, this study collects as much data as possible on their main concerns and the origins of each concern. The contribution of our survey is threefold: It (i) summarizes the available evidence on the specific concerns of actors and criteria they widely use in the selection of market strategies; (ii) identifies gaps in the existing research in order to suggest areas for future studies; and (iii) provides a background allowing to position new research activities. Because it is difficult to compare data from different sources due to possible differences in the study context, research design, collected data, analytical activities, and age of results, the consequences of this survey comprise a collection of relevant information by integrating – rather than comparing – the results of the reviewed studies.

The period from 2000 to 2020 was chosen for this study for the following reasons:

- Addressing the IMM subconsciously brings to mind a list of economic crises with the failure of banks. The publication year of the oldest document found using our search strategy (see Figure 2.2) was 1982. However, many waves of panic have plagued banks before 1982 (e.g. the British crisis of 1825 and US economic recessions in 1837, 1884, and 1907). Nevertheless, the bulk of financial distresses initiated by interbank markets have occurred in the 21st century (e.g. the 2001 Turkish economic crisis, the 2001 Argentine economic meltdown followed by the 2002 Uruguay banking crisis, the global financial crisis of 2007–2008, the 2008–2011 Icelandic financial crisis, and the 2010 European sovereign debt

crisis). Many researchers over the past years have studied the root causes of these crises by looking at IMM structures and mechanisms.

- Although most IMM structures were born in their present form in the 1970s and 1980s (Z. Xu 2006, JICA 2020), interbank lending was not the primary means of managing reserves until the 1990s and was nothing more than a tool of making up for chronic liquidity shortages among banks (Z. Xu 2006). With the use of more modern methods and agreements, such as tri-party repo and other secured loans, in the late 1990s and early 2000s (Choudhry 2011, Seevathian 2016) as well as the 2010s reforms (Copeland et al. 2010, 2014), IMM structures became a tool for central banks to transmit their monetary policies (Freixas and Jorge 2008b, H. Chen et al. 2013). Therefore, research into the concerns of both banks and the central bank, as well as their interaction with each other have grown considerably over the last two decades.
- The results of our supplementary examinations aimed at checking the robustness of findings show that the removal of publications before 2000 has no effect on the list of concerns we have identified in this survey (see Section 2.3 and Appendix B).

The rest of the paper is organized as follows: Section 2.2 states and defines the employed systematic review methodology adapted from Booth et al. (2016) and Petersen et al. (2015). Section 2.3 makes a brief presentation on all concerns (i.e. high-level factors) revealed from our IMM studies database. In Section 2.4, we present a comprehensive thematic survey of literature on the origins of each concern (i.e. mid- and low-level factors) as well as interdependences between the different levels of identified factors with an emphasis on forming a tabular model of the factors and their impacts. In Section 2.5, we articulate the current primary research topics and look at future research agendas. Section 2.6 concludes this paper.

2.2 METHODOLOGY OF SURVEY

The systematic review as the means of evaluating all available research relevant to a particular research question, topic area, or phenomenon of interest (Kitchenham 2004) is the central underlying methodology of this study. Being systematic in the survey helped us in reducing the likelihood of bias and was a way to ensure that a comprehensive body of knowledge on the chosen subject was accurately identified (Booth et al. 2016). As defined by Denyer and Tranfield (2009), a

“systematic review is a specific methodology that locates existing studies, selects and evaluates contributions, analyzes and synthesizes data, and reports the evidence in such a way that allows reasonably clear conclusions to be reached about what is and is not known.”

In this survey, we considered any scientific publication addressing a specific research question in the IMM domain as an *existing study*.

The methodology we used in the survey was based on the framework ‘Search, AppriasaL, Synthesis & Analysis’ (SALSA) recommended by Grant and Booth (2009) for critical steps in the review process. Such an approach ensures rigorousness, fairness, and reproducibility of the review. Adapted from Brereton et al. (2007) and Kitchenham (2004), Figure 2.1 illustrates the review process for this survey to realize SALSA. The process involves ten discrete activities grouped into three main phases (i.e. planning, conducting, and reporting the review).

Since a literature review must be question-led (Booth et al. 2016), we started the first phase by specifying three questions, as discussed in Section 2.2.1. We then established a protocol for the study during the planning phase. This was a document aiming to minimize bias in the study by defining how to conduct the review. It provided a detailed survey plan, specifying the process to be followed in searches, any conditions for selecting primary studies, quality measures, validity checks, and methods for extracting and analyzing data from the literature.

To perform the second phase, we formed a scientific repository for further searches by finding a large number of studies in several scientific databases. We then used an iterative approach so that in the next steps, we were able to find the main underlying terms by analyzing keyword co-occurrences and text mining of titles and abstracts. Consequently, by filtering repository records using these terms and limiting publication dates, we also developed a purposeful list of the studies for detailed review. We also evaluated the selected studies in a few steps, based on the various criteria specified in the protocol. Finally, we extracted and synthesized the data by carefully reading the full text of those documents that passed the inclusion procedure.

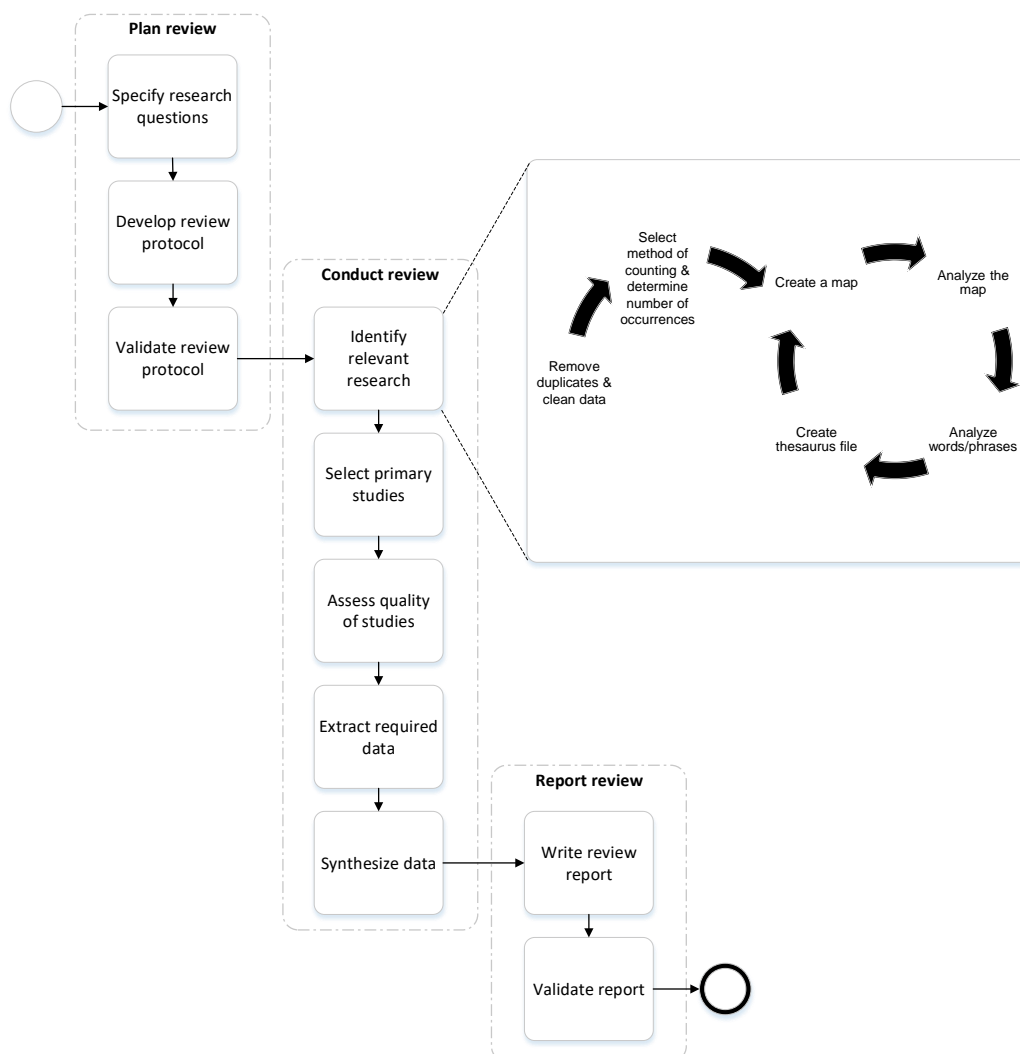


Figure 2.1. Systematic review process used for the survey. The figure shows the sequence of the different steps we took to conduct our systematic review.

In the third phase, we continuously documented the findings step by step and shared them among the entire research team. These reports were reviewed by all members and discussed in the regular meetings we held to monitor the work's progress. Finally, the aggregated comments were combined in the target model, and the review report was summarized to be published.

2.2.1 Research Questions

Due to this fact that an excellent systematic review should be based on a well-formulated, answerable question (Counsell 1997), we employed the 'Population, Intervention, Comparison, Outcome' (PICO) strategy (Santos et al. 2007, Cooke et al. 2012) for the research question construction and evidence search. First, we defined our general free-form question as 'on what basis do the various IMM participants make their liquidity supply/demand decisions?' It was broken down into three research questions exploring the IMM concerns (see Table 2.1).

Table 2.1 shows that in the first stage, to find concerns, we had to look for the most frequent semantic terms in studies restricted to the IMM in which lending and borrowing operations (or supply and demand of liquidity) were considered. It means that studies related to other types of money market (e.g. financial markets in which assets such as certificates of deposit, government bonds, etc. are traded) and other interbank markets (e.g. interbank foreign exchange market) should have been excluded from the searching process and results. In order to answer the second question, searches had to be conducted in the space of the first question and limited to the only identified concerns to find the maximum number of factors inside the IMM environment influencing those concerns. Answers to the third question were limited to the concerns and factors recognized in two previous stages and could have been applied to determine the interdependence between them. Therefore, having a positive or negative effect should also have been considered in finding factors and interdependences when reading publications in detail.

Table 2.1. Research questions formulated for the survey. The different components of PICO to formulate the research questions are shown in the table.

#	RQ	Population	Intervention	Comparison	Outcome
1	What are the main concerns of IMM participants?	IMM participants	Lending or borrowing	Trading money market instruments (e.g. debt, swap, etc.) or exchanging foreign currencies	IMM assets/liabilities (i.e. lendings to or borrowings from other participants)
2	What are the origins of each concern?	Participants' concerns	Influenced by something inside the IMM	Without influence or influenced by something outside the IMM	Effects
3	How do factors affect concerns?	Affecting factors	Influencing concerns	Influencing other things	Positive or negative impacts

2.2.2 Review Protocol

2.2.2.1 Search Strategy

The review considered all research designs and types of publications. Studies conducted on numerical methods, simulation methods, calibrating models, case studies, etc. were all considered. Qualitative research was welcomed, if relevant, as would have published reports and grey literature such as unpublished dissertations/theses/manuscripts and working papers (where accessible) to reduce the likelihood of publication bias. To this aim, both academic and practical published data were collated. Different sources of information in English were queried to maximize the coverage of the search. In order to create a complete database of studies to discover the underlying patterns in the field of IMM and find critical concerns in this domain, the first search terms we chose were related to only the column 'population' for the row #1 in Table 2.1. After several experiments, combinations of the following search terms were applied to the selected databases.

*(inter/ bank) AND (money OR monetary OR market OR network) AND NOT
(foreign exchange OR forex)*

From this combination, the search results were expected to include all studies conducted on possible terms for the research area, from the full phrases (e.g. interbank money market) to the lesser-used expressions (e.g. interbank monetary network or inter-bank market). They did not also contain phrases that we did not want to be seen in the search results (e.g. non-interbank money market or interbank foreign exchange market). Searches were done in titles and abstracts.

Table 2.2. Scientific databases and search strings employed for the survey. The query applied to search in different databases and the search results according to the types of documents are presented.

#	DB	SEARCH STRING	J	WP	T	BC	CP
1	ProQuest	ti,ab(((inter p/0 bank) AND (money OR monetary OR market OR network) NOT (foreign exchange OR forex))	515	317	17	0	5
2	WoS	TS =(((inter NEAR/0 bank) SAME (money OR monetary OR market OR network) NOT (foreign exchange OR forex))	56	0	0	0	45
3	Scopus	TITLE-ABS (((inter W/0 bank) AND (money OR monetary OR market OR network) AND NOT (foreign exchange OR forex))	384	0	0	26	25
4	EBSCO	TI (((interbank OR inter-bank OR "inter bank") AND (money OR monetary OR market OR network) NOT (foreign exchange OR forex)) OR AB (((interbank OR inter-bank OR "inter bank") AND (money OR monetary OR market OR network) NOT (foreign exchange OR forex))	1,033	116	7	58	0
5	JSTOR	ti:(((interbank OR inter-bank OR "inter bank") AND (money OR monetary OR market OR network) NOT (foreign exchange OR forex)) ab:(((interbank OR inter-bank OR "inter bank") AND (money OR monetary OR market OR network) NOT (foreign exchange OR forex))	122	3	0	12	0
TOTAL AFTER REMOVING DUPLICATES AND INCOMPLETE DATA			749	434	24	44	54

DB–Database; J–Journal; WP–Working paper; T–Thesis; BC–Book chapter; CP–Conference paper

Five scientific databases shown in Table 2.2 were employed to create the repository by search results. Our initial repository was created using 1,305 results after

removing duplicates and incomplete data. Additionally, the search was supplemented by the use of Internet meta-search engines. To this purpose, the first 50 hits from searches in Google Scholar and ResearchGate were examined. In addition to the working papers searched on the European Central Bank (ECB) and the Federal Reserve System (the Fed) – if they were absent in the repository – other useful data were provided by the research group members by their experience. Moreover, in order not to miss anything as much as possible, if we came across a publication that referred to a study that was not in our repository at the time of the detailed review, we would add the latter to the repository (see Figure 2.2).

Subsequent searches were all based on words or phrases representing the identified concerns and performed on the records included in the scientific repository created by refining search results. Similarly, the terms used for this group of searches were only relevant to the column ‘population’ for rows #2 and #3 in Table 2.1. In Sections 2.3 and 2.4, we explain how we created a thesaurus for subsequent searches and employed it to prepare a list of search terms.

2.2.2.2 Inclusion and Exclusion

To support the columns ‘intervention,’ ‘comparison,’ and ‘outcome’ in Table 2.1, we filtered out data by a set of exclusion criteria. First, given that we had to keep as much data as possible to perform text mining of titles and abstracts, in order to prepare data for bibliometric analyses, we excluded only preliminary publications (EXC1) as well as irrelevant documents to IMM (EXC2) as described in Table 2.3 (coarse-grained exclusion). For subsequent searches, documents that were not necessarily useful to answer the second and third research questions were removed from the repository using a set of new exclusion criteria alongside previous criteria, as exhibited in Table 2.3, to retain only pertinent articles (fine-grained exclusion).

Table 2.3. Exclusion criteria to prepare data for analyses. The table explains what criteria were used for screening at each stage of the review.

ID	EXCLUSION CRITERION	DESCRIPTION	EXCLUSION STAGE
EXC1	Preliminary publication	The document is extended in another paper by the same authors. The second paper's contributions complement the ones from the first so that the prior is excluded.	Coarse-grained; fine-grained
EXC2	Unrelated to IMM	Documents whose primary focus is not IMM (we mean interbank lending/borrowing market).	Coarse-grained; fine-grained
EXC3	Unrelated to identified concerns	Documents published in the field of IMM that do not relate to identified concerns.	Fine-grained
EXC4	Not indicating effects	Documents that are somehow related to the identified concerns but do not indicate any influencing factors inside the IMM.	Fine-grained
EXC5	Not a recent data	Documents that all the data used belongs to before 2000. It is assumed that the non-recent research is not up-to-date due to the high evolution rate in the field of IMM.	Fine-grained
EXC6	Poster or demo publication	It is assumed that a poster or a demo cannot give enough details on the contributions, as there is no enough contributed content for evaluation. Ph.D. theses and technical reports are included.	Fine-grained
EXC7	Survey paper	It is assumed that the survey papers, book reviews, and discussions do not provide contributions directly to IMM concerns.	Fine-grained
EXC8	Inaccessible document	It is impossible to evaluate a document when the text (i.e. PDF download, online text, etc.) cannot be accessed.	Fine-grained

We identified extended documents first by examining the titles to confirm that the publications were relevant and then again by reading only the abstract of those documents whose relevance was not clear from their title. The result formed a repository of 609 records ready for bibliometric analyses. After conducting bibliometric analyses, when IMM concerns were recognized, relevant information for the detailed review was identified in a three-step approach based on the exclusion criteria described above. In the first step, publications were excluded if their titles were

considered irrelevant based on IMM concerns. In the second step, publications were excluded when their abstracts were considered irrelevant. A conservative approach was used in both steps, meaning that if there were any doubt about the relevance of the information, it would have been retained. The included publications were viewed at the full text in the third step, and all exclusion criteria were checked. Figure 2.2 shows how we used the exclusion criteria to exclude unnecessary data from the repository at various stages.

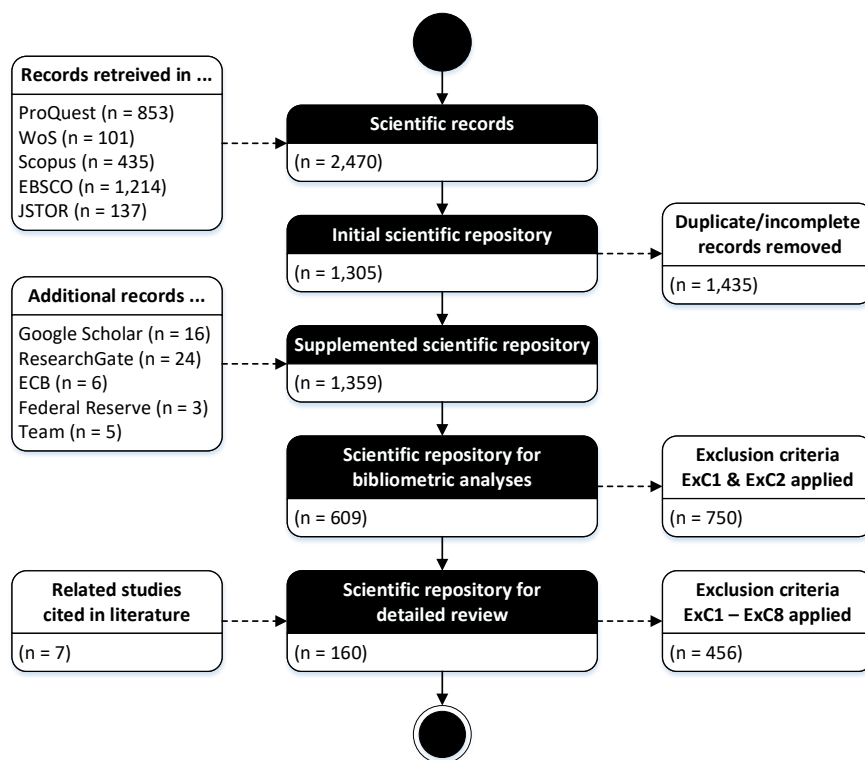


Figure 2.2. Search strategy profile. The figure displays the different stages of screening and the criteria used in each stage.

2.2.2.3 Quality Assessment

Booth et al. (2016) stated that a systematic review relies on quality criteria allowing to assess the quality of primary studies. The quality criteria for this survey aimed to answer the following questions about each document: (i) Do the authors provide a sound rationale (i.e. motivation) for their work? (ii) Is there an adequate description of the

context in which the study has been conducted? (iii) Is there a clear statement of findings and results, including data that support them? Furthermore, (iv) Are the limitations of the study discussed and future directions highlighted? The quality criteria were not applied to exclude/include primary studies. Instead, they were used to report the overall quality of primary studies included by the survey.

In order to mitigate the subjectivity of the reviewing process, we took specific steps to overcome biases and resolve conflicts. In particular, each document was assessed by a reviewer using a quality checklist (see Appendix C) and approved by at least one supervisor. Two other supervisors intervened as referees to resolve possible conflicts. Similar procedures were performed for all the tasks shown in Figure 2.1, and all conflicts were resolved during the regular meetings.

2.2.2.4 Critical Appraisal

In addition to assessing the quality of the studies included (Section 2.2.2.3), their internal validity (i.e. risk of bias) and external validity (i.e. generalizability) were examined, based on Downs and Black (1998). To check the internal validity of studies, we examined whether (i) the results of the study were probably based on data dredging; (ii) the tests used to assess the primary outcomes were appropriate; and (iii) the main outcome measures used were accurate (i.e. valid and reliable). For external validity check, we examined if the study (i) employed real data to obtain the results and (ii) used a distance function or goodness-of-fit metric as formal validation tools. The results of these assessments are reported in Section 2.4.1.1.

Also, in order to guarantee the quality of our research, we complied with the ‘assessment of multiple systematic reviews’ (AMSTAR) criteria (Shea et al. 2007, Shea et al. 2009). For this purpose, we (i) provided an ‘a priori’ systematic review protocol; (ii) removed duplicate and preliminary studies; (iii) performed a comprehensive literature search using five sources; (iv) included grey literature in our search; (v) reported the number of both included and excluded documents at all stages; (vi) provided the characteristics of the included studies; (vii) assessed the quality of the

included studies; (viii) used included studies' quality in formulating conclusions; (ix) applied an integrative approach, adapted from Whitemore and Knafl (2005), to combine the studies' findings; (x) considered the likelihood of publications' bias; and (xi) carefully monitored potential sources of support in studies to prevent the conflict of interest with this survey.

2.2.2.5 Data Extraction

In addition to the studies' authors, the publication date, the publication type, the method employed, and the country or region where the data were gathered were recorded. Also, the relevance of the publications with the IMM concerns was determined in terms of the main focus. Finally, a coding sheet was provided. Moreover, in order to extract and document ideas and results of the reviewed publications, we used a mind map as the primary tool due to many positive feedbacks on facilitating information retrieval and critical thinking (Farrand et al. 2002, D'Antoni and Zipp 2006, Nesbit and Adesope 2006, D'Antoni et al. 2010). All reviewers and supervisors were involved in the data extraction process. For each study, a reviewer extracted the data, and at least one supervisor checked it.

2.2.2.6 Data Analysis

Data were synthesized in two ways. First, extracted data were presented in the form of tables and graphs to provide an overview of the reviewed studies. The studies' findings were then summarized in a narrative report due to the wide variety of themes and data provided by the evaluated publications that differed in the study design and different populations' use.

2.3 RESULTS OF BIBLIOMETRIC MAPPING: THE CONCERNS

As shown in Figure 2.1, we conducted an iterative process to identify underlying IMM concerns through several bibliometric analyses of the included literature. The discovery process described in this section was established on the basis of an ‘information retrieval’ search-based approach (Shepherd et al. 2007). The remainder of this section provides analyses on keywords, titles, and abstracts of all documents in the repository.

As mentioned in Section 2.2.2.2, we used only EXC1 and EXC2 exclusion criteria for bibliometric analyses (coarse-grained exclusion) in order not to lose any concerns. For example, we did not limit the time frame of documents (EXC5) for bibliographic analyses. Instead, we applied this criterion during the full review of the publications to focus better on the documents of the last two decades for the reasons mentioned earlier.

2.3.1 Bibliometric Analysis of Keywords

We first evaluated keywords’ relatedness for all 609 publications (1982–2020) available in the repository to provide a base. It was performed through a bibliometric analysis based on the number of documents in which the most common keywords occurred together. The analysis process itself, as shown in Figure 2.1, was done in several iterations with the aim of finding widely used keywords, identifying synonyms, creating/updating a thesaurus, constructing a bibliometric map, and analysing it.

To calculate the relatedness of the keywords for building a co-occurrence map, we employed the ‘fractional-counting’ method, in which the weight of a co-occurrence link is fractionalized based on the number of other keywords in the publication (van Eck and Waltman 2014). The reasons for this choice are described in detail in Appendix A, along with the details of the relevant calculations.

In order to build a thesaurus, all general terms (e.g. economics and analysis) were removed, and only one particular keyword was used on behalf of several similar terms (e.g. network topology and market structure). The minimum number of occurrences of a keyword was considered 30 (i.e. 5% of all documents), meaning that we searched for keywords that occurred in more than 5% of documents. Of the 1,482 keywords in the first run, 24 met the threshold. Updating the thesaurus and re-executing the counting algorithm continued until 20 top-ranked keywords were neither similar nor general. Figure 2.3 shows four clusters that were finally determined using the software VOSviewer.

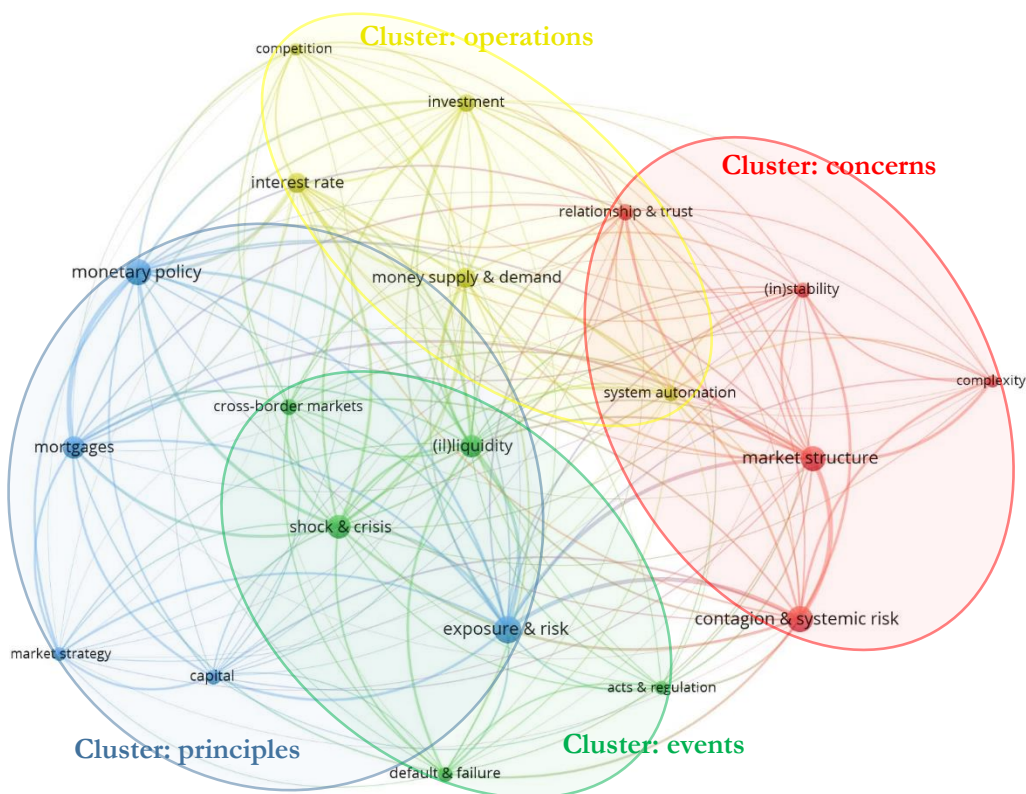


Figure 2.3. Clusters resulting from the keywords co-occurrence analysis. The figure shows the four clusters resulting from the scientometric analysis of the keywords of 609 documents.

We named clusters according to the meaning and nature of most of their keywords. It is worth noting that understanding the dominant nature of clusters was adapted from the generalization of Zachman (1987, 1999)'s enterprise architecture framework to the IMM as a large-scale organization (Barucca and Lillo 2016, 2018).

Accordingly, the study of any ecosystem of any size – from a business unit in a company to a large multinational organization and an extra-large social/ economic structure – could be done in six aspects to answer the questions of what, how, where, who, when, and why. The answers to the two questions ‘where’ and ‘who’ have already been given with ‘the interbank market’ and ‘the market players,’ respectively. As explained for the thesaurus building process, all the terms related to these two questions were removed from the list of keywords studied to reduce both the computational load and complexity of maps.

Adapted from Zachman (2003), we recognized that the first three clusters were related to the principles (why: motivation), operations (how: process), and events (when: timing) of the market, which form the concrete structure of the body of knowledge in this field. For instance, the monetary policy and macro-prudential regulations adopted by the central bank as well as the counterparty risk and other micro-prudential issues of banks are the most critical drivers in implementing lending or borrowing strategies and behaviors in the market. Capital and loans (i.e. interbank mortgages) are also considered market infrastructures and are among the principles. As for operations, the market’s primary functions include the supply and demand for money through lending and borrowing. All possible mechanisms, including auctions held by the central bank to strengthen the competition between banks to take advantage of the central bank’s money, and different interest rates offered by buyers and sellers fall into this category. In times of economic crises, market shocks, foreign interbank market events, or changes in rules and regulations, market participants have to adapt to new circumstances by choosing the right strategy. We thought that the fourth cluster would have addressed those market concerns (what: inventory) that may change over time so that market players must continuously monitor them and take action to formulate policies or adopt appropriate strategies. Our decision to name this cluster as ‘concerns’ was mainly based on our experience in this field and relative awareness of recent concerns in financial markets.

At the keyword level, five terms ‘contagion and systemic risk,’ ‘market structure,’ ‘relationship and trust,’ ‘stability,’ and ‘complexity’ were included in the so-called

concerns cluster. By contagion and systemic risk, we mean the interdependence of banks, and transmission of risks across the whole of the market. The market structure includes all topics related to network topology and market configuration, while relationship and trust are connected with the history of all fiduciary relationships between market players. By stability, we mean the state in which the IMM is resistant to economic shocks and is fit to smoothly fulfill its basic operations to address the worries about volatility in prices and rates in the market and have a stable environment for the operations of money supply and demand. Finally, complexity includes all keywords related to complex systems and networks.

2.3.2 Bibliometric Analysis of Titles and Abstracts

After establishing the foundations of the market concerns and setting the initial scope, we expanded it, as shown in Figure 2.4, by identifying new concerns in publication texts. Due to these facts that frequent words characterize texts better than keywords (Conway 2010) and that the abstract, as a summary, contains a higher frequency of relevant terms than keywords (Shah et al. 2003, Noh et al. 2015), and also, because of the importance of title for condensing content in a few words, we focused on text mining of publications' titles and abstracts at this point.

We provided a term co-occurrence map based on titles and abstracts of all 609 publications (1982–2020) available in the repository through several iterations to determine the highest frequent terms, complement the thesaurus, and create a new map. In each iteration, a term map was provided with the help of the software VOSviewer. The software performed a term identification process in three steps: (i) applying a linguistic filter to the corpus in order to identify noun phrases, (ii) measuring the unithood of noun phrases in order to identify semantic units, and (iii) measuring the termhood of semantic units in order to identify terms (van Eck et al. 2010, van Eck and Waltman 2011). In this co-occurrence analysis of terms, the relatedness of the identified terms was determined based on the degree to which they were used in the same publications. The more often two terms occurred in the same publications, the

the failure to meet the legal obligations of a loan, has been moved from events to concerns. This might be since, in IMM publications, default is generally considered the starting point for contagion, leading to default cascades of other members and market instability; it is closely related to systemic risk issues. Also, the keyword ‘complexity’ has been removed from the list of concerns. This might be because, despite this word’s existence in the keywords, documents try to support it in the text using scientific, innovative tools and techniques described in other words. By integrating the findings of these two steps of the study, the main concerns of the market can be considered in the form of five themes ‘contagion and systemic risk,’ ‘stability,’ ‘market structure,’ ‘relationship and trust,’ and ‘default and failure.’

We also repeated these two analyses by applying the EXC5 criterion (i.e. exclusion of documents published before the last two decades) to the literature in our repository. The results of the bibliometric analyses on this new dataset are presented in Appendix B. Figures B.1 and B.2 show that there is no significant difference between the clusters of concerns in the two cases.

2.4 RESULTS OF INTEGRATIVE REVIEW: THE AFFECTING FACTORS

This section deals with the results and discussion from a detailed review of the total sample of 160 publications regarding the factors affecting the five concerns identified in Section 2.3. According to our method (see Figure 2.1), the identified concerns were considered particular themes, and the publications on each concern were reviewed in detail to discover the factors that reinforce/undermine them and evaluate the publications’ quality (as per Sections 2.2.2.2–2.2.2.4). This detailed review results, along with a summarized table of factors, impacts, and strategies, are presented in this section. Before that, descriptive statistics are presented in tabular and graph form to understand this field’s evolution in the last two decades. All statistical data and maps

are provided using the Bibliometrix R-package developed by Aria and Cuccurullo (2017). We also used MS Excel to draw charts.

2.4.1 Demographic Data

2.4.1.1 Basic Summary of The Sampled Publications

(a) General View

The forthcoming findings (Section 2.4.2) result from an integrative review of 136 journal articles, 17 working papers, 4 conference papers, 2 theses, and 1 book section. The general information about this collection of publications is shown in Table 2.4.

Table 2.4. Characteristics of the selected publications. The table summarizes characteristics of the 160 selected documents.

Variable	Description	Results
Timespan	The total number of years within which the various data spans of the studies fall	2000–2020
Sources (journals, books, etc.)	The number of sources from which the documents were derived	88
Average years from publication	Average years to a document to be cited	5.06
Average citations per documents	The result of dividing the total number of citations by the number of documents	91.63
References	The total number of references used by documents	6,293
Average references per documents	The result of dividing the total number of references by the number of documents = 6,293/160	39.33
Authors	The total number of different authors appearing in the selected documents	324
Author appearances	The total number of authors appearing in the selected documents (note: one author appearing in two papers counts for two authors), calculated as the sum of the number of authors appearing in each paper.	423

Authors of single-authored documents	The number of authors authoring alone (as single authors)	21
Authors of multi-authored documents	The total number of authors contributing to documents with more than one author	303
Single-authored documents	The number of documents that have been authored by one author	23
Multi-authored documents	The number of documents that have been authored by more than one author	137
Documents per author	The ratio of the total number of documents divided by the number of authors = $160/324$	0.494
Authors per document	The ratio of authors over the documents = $324/160$	2.02
Co-authors per documents	The ratio of author appearances over the documents = $423/160$	2.64
Collaboration index	The result of dividing total authors of multi-authored articles by total multi-authored articles = $303/137$	2.21

(b) Included/Excluded Documents

Figure 2.5 (a) plots the total number of excluded studies per exclusion criterion, separated by coarse- and fine-grained steps. In the coarse-grained step, the discarded data for bibliographic analyses consisted of 14% of all studies in the repository (1,359 documents) because they were the original version of the research, which were later completed, plus 41% that they were irrelevant to the scope of IMM. In the fine-grained step, the most common causes for filtering out were first, the irrelevance of the studies to the concerns discovered through bibliographic analyses (44% of the remaining 609 documents) and then the lack of indication of at least one effect in the publication (12% of the 609 documents).

(c) Quality of Studies

Based on the quality criteria defined in Section 2.2.2.3, we evaluated the quality of each publication in terms of (i) the problem mentioned and the authors' motivation; (ii) the study context, containing the use of sufficient resources and method description; (iii) full explanation of data as well as theoretical and experimental results; and (iv) the

limitations and future directions of the research. Figure 2.5 (b) shows the average evaluation of criteria for the total publications as well as for each concern. According to the quality assessment process described earlier, for each publication, after it has been evaluated by the reviewer and approved by the supervisors, each criterion has been given a score of 1 to 5 based on our quality checklist (see Appendix C).

According to the results of the quality assessment process, over the entire set of documents, data and results are clearly explained by the authors. Motivations and context are presented with an acceptable set of details to allow readers to understand the basics of the topic and the results presented. Finally, as shown in the figure, the research team has considered the limitations of the proposed models and approaches that are not sufficiently detailed within the publications.

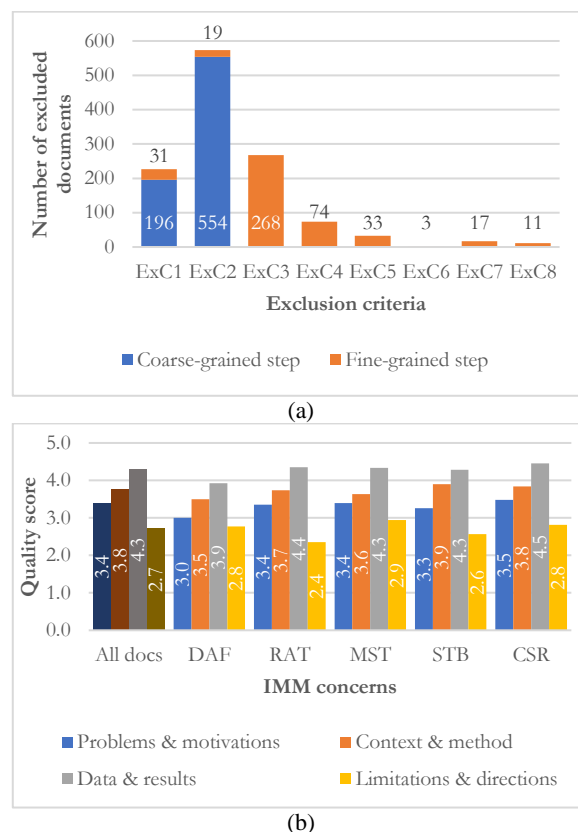


Figure 2.5. (a) Excluded documents per excluded criteria; (b) Quality scores of studies per IMM concerns. Subfigure (a) presents a comparison of different exclusion criteria in terms of the number of excluded publications. Subfigure (b) shows the average scores assigned to documents devoted to different concerns.

The average quality score of all documents is 3.5. The publications related to the two concerns ‘contagion and systemic risk’ (CSR) and ‘market structure’ (MST) are of overall better quality (3.6) than the documents of the other concerns. The publications related to ‘stability’ (STB) and ‘relationship and trust’ (RAT) are in the next ranks with an average score of 3.5 and 3.4, respectively. The most inferior quality also belongs to the documents related to concern ‘default and failure’ (DAF) with a score of 3.3.

The persistent pattern in the sub-scores for each of the classified factors shown in Figure 2.5 (b) may be related to the fact that a very clear boundary between concerns cannot be drawn since there are many researchers who are authors in more than one field (e.g. Li S., Iori G., Georg C.P., etc.). Nevertheless, although they are small there are some differences in the scores of the criteria in various areas. More maturity in terms of ‘problem and motivation’ in the field of ‘contagion and systemic risk’ than other fields may be due to greater competition among researchers in this field to assert their knowledge of the domain and its problems as well as the applicability of their research. It is noted that this field has the largest number of documents, which shows the willingness of researchers in recent years to conduct and publish research in this area (see also Figure 2.10 (a)). Comparing the ‘data and results’ score in different domains, it seems that the concern ‘contagion and systemic risk’ is in a similar situation in terms of data availability and, consequently, the presentation of more diverse results. In terms of ‘context and method,’ the highest score is given to ‘stability,’ which can be due to the use of more refined research methods in this field. Having the largest share of using network analysis methods (33%), agent-based modeling (48%), and game theory (33%) by documents in this field compared to other areas confirms our view. Most reference to the ‘limitations and directions’ of research in the field of ‘market structure’ may be due to the multiplicity of previously mentioned methods for network analysis, which prompts researchers to both consider more assumptions for network simplification and suggest more research opportunities to overcome these limitations in the future.

(d) Internal/External Validity of Studies

In order to assess the risk of bias as well as the generalizability of the studies, as described in Section 2.2.2.4, we have evaluated five measures for each publication. Regarding the first internal validity measure, data dredging bias generally refers to finding and reporting an attractive result without accurately conveying the course of analysis. Therefore, for each concern, we have identified the documents that provided results supported by less than 5% of them as possible cases of data dredging (G.D. Smith and Ebrahim 2002). For example, in the case of the contagion and systemic risk concern, containing 50 publications, when only one or two documents report an influential factor, those are identified as possible data dredging cases. To check the appropriateness of the methods and the accuracy of the results of each study (i.e. second and third internal validity measures), we relied on the criticisms of other researchers, if any. In this way, if others have criticized the method used or the results obtained in a document, we identified it as a possible case for bias. Regarding the first external validity measure, we also relied on the explanations provided in the document about the use of real data. Finally, we checked the use of methods, such as Kolmogorov–Smirnov test or likelihood ratios, to evaluate the second external validity measure. The results are depicted in Figure 2.6.

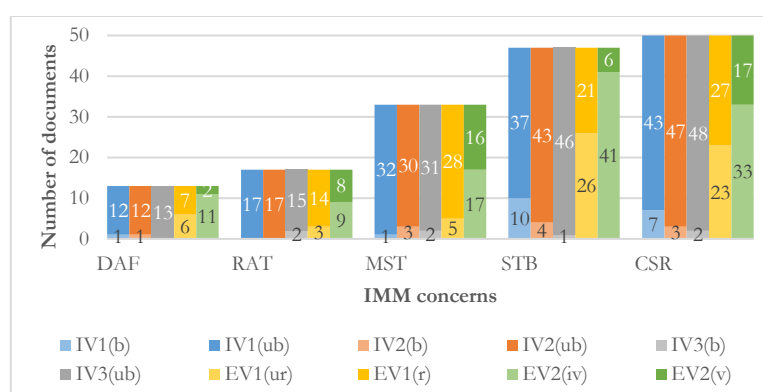


Figure 2.6. Status of internal and external validity of studies per IMM concerns. The figure compares publications devoted to different concerns in terms of internal and external validity metrics (b–biased; ub–unbiased; r–real; ur–unreal; v–valid; iv–invalid).

Considering the total publications, the highest possibility of internal bias is related to data dredging with 19 possible cases, 12% of the total documents. Among the concerns, the highest percentage of data dredging belongs to ‘stability’ (21% of relevant documents) with ten possible items. Our reviews also reveal that 7% of the models and methods applied by the researchers in this field, as well as 4% of the results obtained by them, have been criticized by some other researchers. The results of examining the external validity by evaluating the use of real data in studies show that the authors have employed real datasets of various countries to produce 61% of the publications. Documents produced under the concern ‘market structure’ lead the way with an 85% share (28 publications). Besides, looking at another measure of external validity, namely formal validation, it is clear that in only 31% of cases, the authors have proven the validity and/or reliability of their research, and this measure has been neglected in other cases. The highest compliance level with this measure is still observed in the documents related to concern ‘market structure’ that includes 16 publications (48% of relevant documents).

(e) Research Approaches Applied by Studies

Although qualitative studies were welcomed, all the publications that finally remained in our repository after passing the filtration steps (i.e. exclusion criteria) are of the quantitative research nature. Figure 2.7 compares the quantitative methods used in publications. It is worth noting that many documents use more than one research method, and therefore the sum of them is more than the number of publications. As shown in the figure, 67 studies have been conducted using network models and analyses, which is 42% of the total documents. This suggests that the mainstay of research into IMM concerns is network theory and related methods.

Various regression tests, which have been used as the main method or to complement to other methods in 49 studies, are in second place with 31% by weight and are followed by agent-based simulations (27 documents, 17%). According to the figure, it is clear that planning methods, such as linear programming and dynamic programming, as well as cause and effect analysis methods, such as quasi-experiment

and Granger causality, are less popular among researchers in this field. These methods, plus a number of other less popular methods, have been used in a total of 17% of all publications.

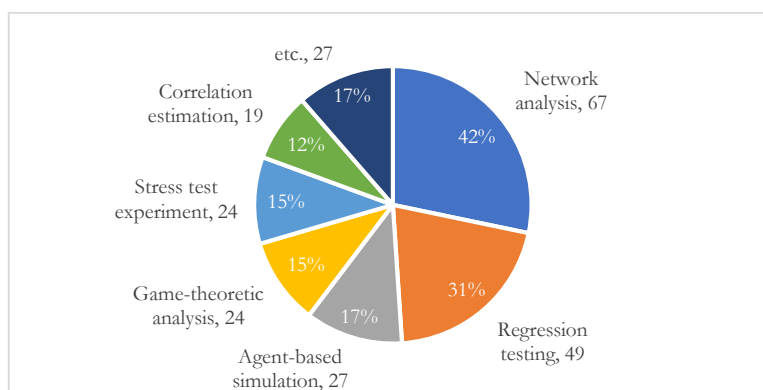


Figure 2.7. Research methods used by studies per IMM concerns. The figure compares different scientific methods employed in the publications.

2.4.1.2 Geographical and Author Collaboration Perspective

Figure 2.8 shows the country's scientific production of documents in this field based on the authors' affiliation. Numbers in different countries indicate the number of authors from those countries who have participated in producing the documents. The thin and thick connections between the countries on the figure express the intensity of authors' collaboration from those countries in producing joint documents. The allocation clearly shows the lead of developed countries in the field. This might be because the authors of these publications acknowledge the interbank market as an essential pillar in the countries' economies for which they study. On top of all countries, we observe the United States is the highest producer of IMM concerns research with 52 studies, followed by Italy with 49, the United Kingdom, and China with 48 studies.

In terms of the use of countries' IMM real data in the production of documents, Italy leads with 21 cases (13%), followed by the European Union with 14 (9%), the

United States with 12 (7%), and Germany with 9 (6%) publications. As can be seen, there is a significant difference between the statistics of using some countries' interbank market data as an indicator that more strongly expresses the dependence of research on those countries with the numbers on the figure. Combining these statistics with the cross-country connections shown in Figure 2.8, it seems that the allocation from this figure should be read more carefully as some economies may facilitate researchers' access to interbank market data or have significant research grants, which may redirect their research priorities toward a particular economy. For example, the high level of communication between the United States and various European countries, especially Italy, and attention to the above statistics could indicate that a large number of American researchers have been involved in joint research conducted by Italian researchers using data from the Italian banking system. Of course, we do not have this background information, and this can only be considered a suggestion for an opportunity for further research.

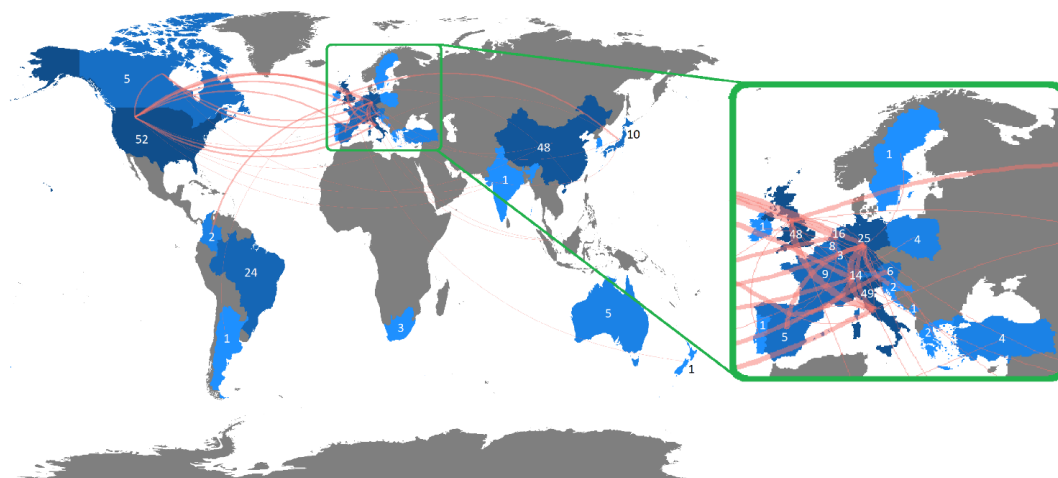


Figure 2.8. Scientific production in IMM concerns area across the globe. The figure shows the country's scientific production of documents based on the authors' affiliation.

Figure 2.9 (a) renders the top ten countries in which most publications in IMM concerns have stemmed. By the origin of the publication, we mean the country of the author's affiliation. Thus, the figure identifies the ten leading countries of origin from which the publications related to IMM concerns have stemmed. Once again, we find that the developing countries are the primary users of IMM, and therefore, they are

more interested in investigating the issues. The interest of all Chinese authors in collaborating with only other Chinese authors, and on the contrary, the desire of all Belgian authors to collaborate with authors from other countries, are also remarkable in this figure.

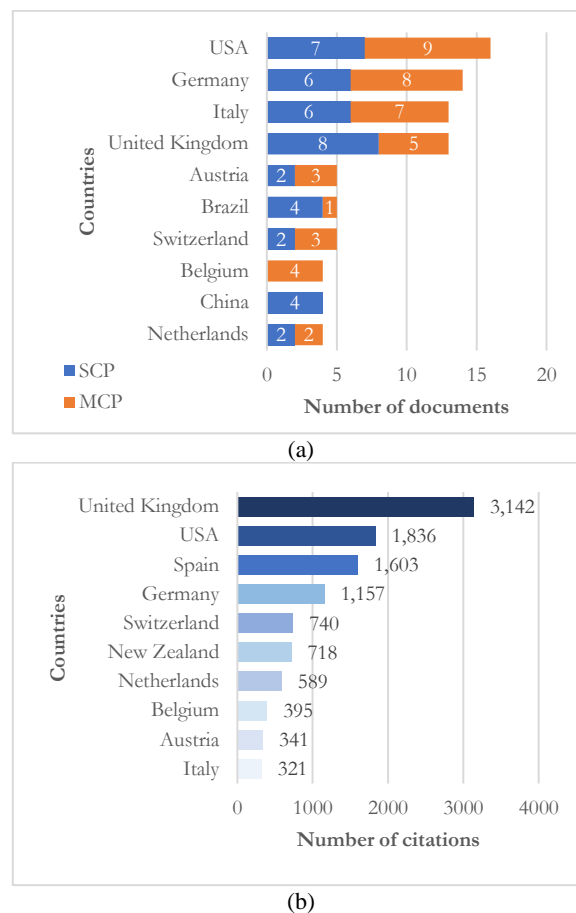


Figure 2.9. (a) Corresponding authors' countries; (b) The most cited countries. Subfigure (a) lists the top ten countries with most publications on IMM concerns. Subfigure (b) lists the top ten countries whose publications on IMM concerns are most cited by other authors.

In terms of the most citations, from Figure 2.9 (b), it identifies the top ten countries that the publications stemmed from which have received the most citations from scholars in the field of IMM concerns. The fact that the United Kingdom tops the list is because of the presence of scholars such as Iori G. and Nier E. (see Section 2.4.1.4) and that the United States follows is due to the presence of Acemoglu D. is relatively consistent with the left part of the figure. Also, Spain, which is not on the

left chart, ranks third on the right chart due to citations to Freixas X.'s work. One of the remarkable things about Italy is that, despite being second in Figure 2.8 and third in Figure 2.9 (a), it has dropped to 10th in Figure 2.9 (b). This reveals that the publications originated by researchers in this country, despite their active participation in the production of science either on their own accord or with the cooperation of researchers from other countries and despite having the most referenced dataset of IMM transactions, have not been as popular as the publications of other countries active in this field.

2.4.1.3 Time Evolution of the Studies

According to Figure 2.10 (a), there is a delay in addressing IMM concerns as a research area, which can be attributed to various reasons. One possible reason could be the lack of objective manifestation of notions like systemic risk and stability before the global financial crisis, which after the emergence in 2007–2008, highlighted new concerns such as market network, the crisis of confidence, and cascading defaults. As seen in Figure 2.10 (a), since then, the upward trend in scientific document production in this area has begun, and after the European debt crisis, it has gradually intensified since 2011. Averagely, the annual growth rate of scientific production in this field is 13.8%, which is sufficiently higher than the 3.9% average annual change of science and engineering (S&E) articles in the world (NSF 2018). Another reason could be attributed to unconventional monetary policies adopted by the ECB after the recent liquidity crisis as well as the publication of the Basel III Framework in 2009, which led to the production of numerous papers examining the effects of these reforms on risk reduction of the banking system. Besides, the maturation of electronic payment/trading infrastructures, which made it easier for researchers to access and use some parts of real data in their research, could be another reason.

A closer look at Figure 2.10 (a) reveals that the first articles were published in 2008 on the concern 'market structure' and in 2009 on the concerns 'default and failure' and 'relationship and trust' and that in the later years, there are fewer fluctuations in the

publications in these three than the other two concerns. The figure also depicts the increasing and visually correlated trend in the production of documents related to the two concerns 'contagion and systemic risk' and 'stability' over the past two decades, which has reached their peaks in recent years. According to this chart, the peak of scientific production in the field of stability is in 2016, after which it seems that this focus has shifted more to the field of systemic risk, to the point that in 2019 we see the maximum production of documents in this field.

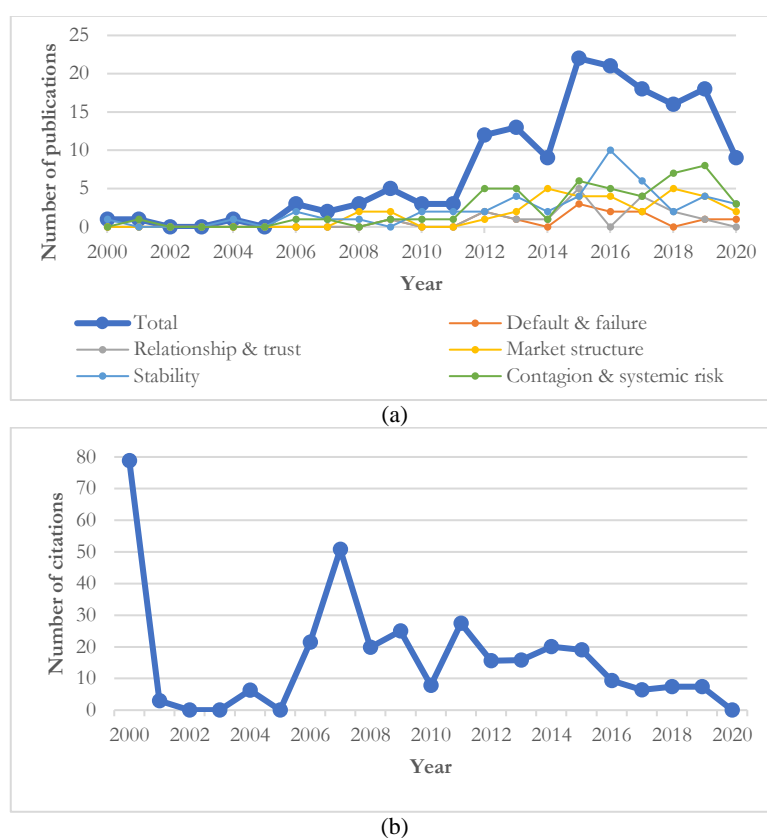


Figure 2.10. (a) Annual scientific production in terms of IMM concerns; (b) Average citations per year. Subfigure (a) shows the number of scientific publications focused on the IMM's five concerns in total and separately for each concern. Subfigure (b) provides a comparison of the number of citations to publications in different years..

In terms of the number of citations to the publications reviewed in this survey, which was extracted from Google Scholar on September 27, 2020, Figure 2.10 (b) shows the evolution of the average document citations per year in the field of IMM concerns. There is a clear downward trend from 2000 to 2005 and again from 2007

towards today, which is normal because older publications are expected to be cited more than recent ones that many readers have not yet read.

2.4.1.4 Prolific Authors, Influential Sources and Publications

(a) The Most Prolific Authors

Publication producing productivity of the top ten IMM concern authors is measured in four ways in Figure 2.11. The first measure exhibited in the subfigure (a) is the number of publications in which each name appears as an author. However, since each author's contribution is reduced when several authors collaborate in producing a publication, we also apply a second measure shown in the subfigure (b), which counts the number of fractional publications. This number adjusts productivity with the total number of authors of each paper. The third measure in the subfigure (c) presents the total citations of one author in the IMM concerns field, and the fourth is the author's h-index (i.e. the author has published h papers that have each been cited at least h times) on this specific field depicted in the subfigure (d).

Subfigures (a) and (b) show that Li S. not only has the highest number of publications but has also participated in producing documents with fewer authors. Also, the lowering of Iori G. from second place in the subfigure (a) to third in the subfigure (b) confirms that some of the documents produced by this author have been provided with the collaboration of a considerable group of researchers. Finally, looking at the subfigures (c) and (d), which focus on the number of citations to documents produced by the authors, we come across several names that do not exist in the subfigures (a) and (b). None of the authors have a stable rank, so the different names interchangeably appear in different positions in every metric. The only author seen in all four subfigures is Iori G. In this regard, based on their position in the metrics, Li S., He J., Thurner S., Tabak B.M., and Battiston S. have the next ranks, respectively,

due to their presence in the three metrics. Hence, these six authors can be considered the most prolific ones in the field of IMM concerns.

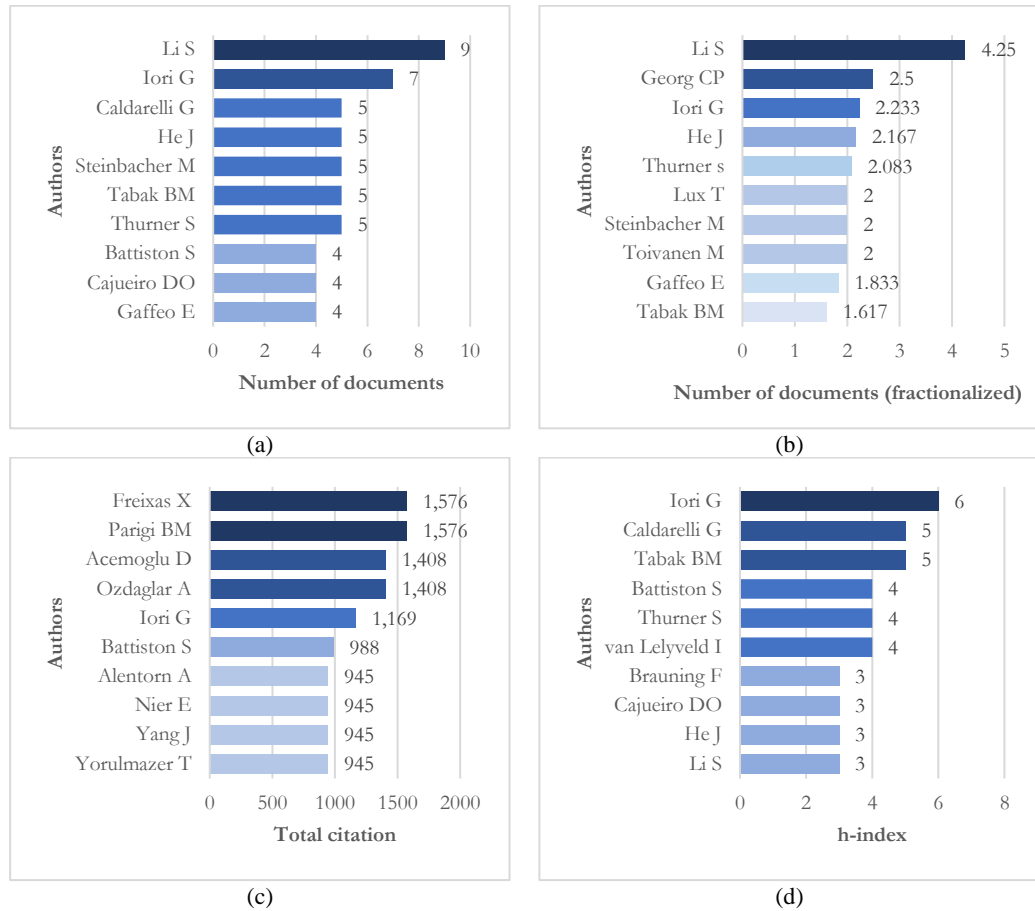


Figure 2.11. Authors' productivity in terms of number of documents (a: full-counted, b: fractionalized), (c) total citations, (d) h-index. Subfigures display the top ten authors (a) whose names are most apparent in all publications, (b) whose names are most repeated considering the number of their col-authors in all publications, (c) whose names are most cited in the literature, and (d) who have the highest *h*-index among all authors.

(b) The Most Influential Sources

As mentioned earlier, 136 of the total publications reviewed, i.e. 85% of the resources, are articles from 65 journals. Of these, 52 journals, i.e. 80% of all journals, containing 121 papers, are indexed in ISI, with an average impact factor of 2.128 based on 2019 data. The Journal of Financial Economics has the highest impact factor (5.731), while the lowest (0.500) is for Pacific Economic Review. In terms of 2019 SCImago journal

ranks, the average SJR score is 1.898, and American Economic Review with the impact factor of 5.561 has the highest SJR scores (13.773).

Besides, identifying the primary sources of knowledge in each specific field of research is useful for future researchers in that field. To do this, we used Bradford's law (Bradford 1934) to classify sources and identify the core zone. This method divides the sources into three zones according to the number of publications so that in each zone, it is approximately equal. The core zone consists of six journals, covering a total of 53 articles (33% of the total number of sources), compared to the second and third zones with 30 and 52 sources containing 55 and 52 publications, respectively. The titles and specifications of the six journals categorized as the cores are listed in Table 2.5. A comparison between the number of citations to documents published in the sources of each of these three zones revealed that the number of citations in the core zone also accounts for about one-third of the total citations (4,746 citations equal to 32% of the total citations). The number of citations to the second and third zones' publications is 7,941 (54%) and 1,974 (13%), respectively.

Table 2.5. The most influential sources in the field of IMM concerns. The table lists the six core journals identified through Bradford's law.

#	Source	Number of articles	Total citations	<i>h</i> -index (local)	Impact factor	SJR score
1	Journal of Economic Dynamics and Control	13	2,717	11	1.204	1.169
2	Physica A: Statistical Mechanics and Its Applications	12	522	8	2.924	0.712
3	Quantitative Finance	10	451	8	1.491	0.691
4	Journal of Banking and Finance	7	658	6	2.269	1.344
5	Journal of Financial Stability	6	251	6	2.451	1.627
6	Advances in Complex Systems	5	147	3	0.976	0.275

(c) The Most Influential Publications

Figure 2.12 shows the top ten most cited articles in various time periods based on the total citations per year. The number of citations from a publication is a critical factor that shows how instructive the methods used and the findings of that publication have been for peers and readers, and to what extent it has been effective in producing later threads of science in that field. Because, on the one hand, new publications need time to reach readers and receive more citations over time, and on the other hand, very old publications may not be as citational as before, we applied the total citations per year to our analysis. The bubble size in the figure indicates the relative value of the total citations per year. The most citations are by Acemoglu et al. (2015) with 1,408 total citations and 234.7 citations per year, followed by Battiston et al. (2012) with 743 and 82.6, and Freixas et al. (2000) with 1,576 and 75.0 total citations and citations per year. Future researchers may find it interesting to read these influential articles.

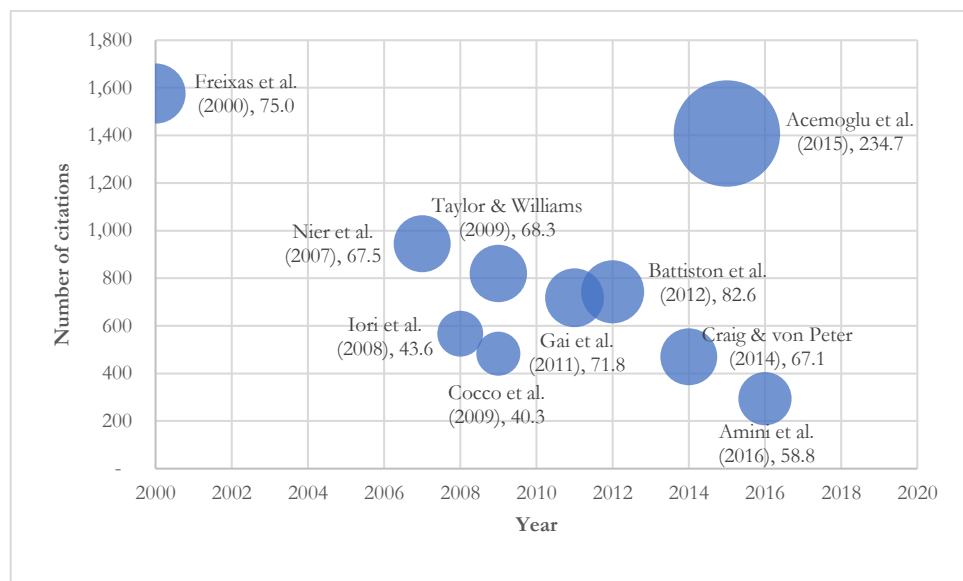


Figure 2.12. The most influential articles published in different timeframes. The figure displays the top ten most cited articles in various time periods based on the total citations per year.

In order to evaluate the relationship between the two variables, total citations per year and publication lifetime, we used a regression test. The result suggests that despite

the noise and high variability in the data ($R^2 = 0.062$), the publication lifetime is well able to predict the total citations per year. This relationship is formulated as $TCPY = 3.166 + 1.558t$ with both slope and constant as significant at 0.002, where $TCPY$ denotes the publication's total citations per year and t , which is measured as the distance from today (2020), denotes the publication's lifetime. This equation shows a positive trend between lifetime and total citations per year, which indicates that the research community is interested in the IMM concerns field.

2.4.2 Affecting Factors

2.4.2.1 Market Structure

Interbank lending connects banks in the form of a network, which is one of the critical factors in transmitting shock and triggering systemic risk in the market (see Sections 2.4.2.4 and 2.4.2.5). This is the third identified concern for the IMM in terms of the number of publications. We address this first as it would help to provide a synopsis of how the IMM generally functions before discussing how strategies can change due to stress and contagion. Like many real-world networks, the interbank network is mainly characterized by nodes (i.e. banks), links (i.e. the reciprocal exposures), size (i.e. the number of nodes), and connectivity (i.e. the number of links relative to the number of possible links). Other topological characteristics include link weights, node strength, degree distribution, clustering coefficient, node centrality, etc. Many researchers attach particular importance to the IMM network structure in determining the spread of contagious defaults (Imakubo and Soejima 2010a, Li and He 2011, Mastromatteo et al. 2012, Pecora et al. 2016, Barucca and Lillo 2018, Cuenda et al. 2018, Brunetti et al. 2019). Several of them have considered network models as a tool to form links in order to reduce the risk of contagion (Leitner 2005, Babus 2016), and through this, they want to rationalize the IMM network as an insurance mechanism.

Network simulation studies have provided a practical basis for more directly quantifying the impact of network features on IMM concerns as well as examining the impact of a range of other factors, including asset fire-sales (Zhang et al. 2018, Calimani et al. 2019), rollover risk and portfolio overlap (Anand et al. 2012, Fique and Page 2013), regulatory taxation (Zlatic et al. 2015, Poledna and Thurner 2016), etc. This section attempts to find the factors affecting the IMM network structure throughout the literature in this field. While many of the factors reviewed in this section can lead to changes in the current state of an interbank network (i.e. forward change), some of them are able to reverse these changes (i.e. backward change) and some lead to the emergence of a new form of network (i.e. formative).

(a) Liquidity Availability

Since liquidity is the main material transferable in the interbank network – and the connections between nodes represent this material’s flows – its availability in the IMM plays a key role in shaping the network. The two main events that most affect market liquidity are the occurrence of *shocks* and financial crises as well as liquidity *injection* by the central bank in the market. The IMM network’s behavior in dealing with shocks and during financial crises is twofold. On the one hand, links in the network transmit the shock among nodes, and on the other hand, the strategies adopted by nodes to deal with the shock lead to changes in the network’s shape. The latter, as a feature considered by most researchers in the field of factors affecting the IMM network structure, is reviewed in this section. Also, regulatory intervention in the market, leading to the adoption of stabilization policies, is a means that neutralizes the adverse changes caused by shocks in the market structure. In the literature, this includes both direct central bank intervention in the market to provide liquidity and crosscutting policy changes.

Theoretically, the simulations performed by Fique and Page (2013) highlighted the existence of a structural break in the last quarter of 2008, meaning that the deteriorating fit of the core-periphery structure in the post-crisis period was mainly due to the loosening of connections in the core, particularly on the lending side. Also, Acemoglu

et al. (2015) found that the topology of financial networks most prone to contagious failures depends on the number of adverse shocks that affect the financial system. In another simulation using the agent-based approach, T. Xu et al. (2016a) stated that shocks are causes for individual nodes' failure and, consequently, the interbank network changes.

Empirically, using data from the Eurosystem's payment system TARGET2, Gabrieli and Georg (2014) examined liquidity allocation among European banks in 2008 and found that following the Lehman Brothers' insolvency, the aggregate change in liquidity reallocation (liquidity shock) in the overnight market due to liquidity hoarding by lenders and maturity shortening of their interbank lending led to a substantial structural change so that the interbank network shrank. A large number of researchers examining the interbank markets of individual European countries obtained similar results. For instance, using data of interbank exposures in the Netherlands, first Squartini et al. (2013) and then in 't Veld and van Lelyveld (2014) and Blasques et al. (2018) discovered that the Dutch IMM structure considerably changed after the adverse shock and during the financial crisis, as was also found by Fricke and Lux (2015), Pecora et al. (2016), Affinito and Pozzolo (2017), Barucca and Lillo (2018), Kojaku et al. (2018), and Brunetti et al. (2019) for the Italian IMM. In the case of non-European countries, Vandermarliere et al. (2015) found that as the Russian IMM moved from a 'normal' to a 'crisis' period, the network topology changed significantly. Another study by Brassil and Nodari (2018) on unsecured overnight loans in Australia revealed that the 2007–2008 financial crisis had a large, long-lasting effect on the IMM network: the core shrank and reduced exposure to the periphery, while the periphery switched from a net borrower to a net lender.

In their study of banks' rollover decisions, Figue and Page (2013) dynamically modeled the policy measure as the cost of activating interbank connections and found that a significant reduction in policy level is needed for network recovery and lending restart when the market is severely stressed. Using an agent-based model to calculate banks' dynamics in the IMM network, Halaj and Kok (2015) proposed a sequential network formation mechanism to examine how key parameters affect IMM structures.

They observed that macro-prudential policies had significant impacts on network formation. Another study that addressed the nexus between liquidity policies and financial networks was conducted by Wegner (2019). The results of this study showed that government and central bank policies that promote market liquidity could lead to the emergence of financial networks that are better capitalized while being more fragile. Three separate studies by Affinito and Pozzolo (2017), Barucca and Lillo (2018), and Brunetti et al. (2019) using Italian IMM data in the platform ‘electronic market for interbank deposits in the Euro area’ (e-MID) confirmed that Eurosystem’s ‘open market operations’ (OMO), especially ‘long-term refinancing operations’ (LTRO), after the Europe economic crisis of 2010–2012 were associated with a shift back to the earlier IMM structure. They argued that this was due to the changes in banks’ strategies when LTROs were implemented. Moreover, by analyzing the Turkish IMM data, Sümer and Özyıldırım (2019) concluded that the central bank’s efforts to restore liquidity in the IMM during and after the global financial crisis increased the central role of foreign deposit banks in the network against the Turkish state and large private banks.

(b) Banks’ Characteristics

Various *characteristics of banks*, as interbank network nodes, play various roles in shaping the network. Using Brazilian IMM data, once Cajueiro and Tabak (2008) had demonstrated the role of origin (domestic or foreign), control (public or private), and sector (retail, treasury, business, or credit) as dimensions of banks, Cajueiro et al. (2009) showed the effect of size (large or small) of banks on the network structure. For example, they argued that if smaller banks borrow or lend in the IMM beyond their capacity, network changes are more severe or that the bankruptcy of a medium-sized bank could lead to significant network changes. Many other scholars have also investigated the effects of banks’ size on the market structure. Results of examining the IMM network structure for Italy by De Masi (2009), Australia by Sokolov et al. (2012), the Netherlands by in ’t Veld and van Lelyveld (2014), Chile by A.J. Sun and Chan-Lau (2017), Colombia by León et al. (2018), and Turkey by Sümer and Özyıldırım

(2019) revealed that in all these networks, larger banks make the network's core, and smaller banks are the leaves.

Similar findings by Ben R. Craig and von Peter (2014) led them to conclude that tiering in the German IMM is not random but behavioral and correlated with size. They also found that the core includes national or international banks that provide a broader range of financial services than local or special-purpose banks. The simulation performed by Lux (2015) yielded similar results, including the fact that for heterogeneous balance sheet sizes, the self-organization of the interbank lending network toward asymmetric core-periphery structure was revealed, which was very similar to established structural features of interbank credit relationships. Also, T.C. Silva et al. (2016) showed that large banks in the Brazilian IMM network tend to form near-clique structures (complete graphs).

(c) Information

Another essential factor that plays a role in shaping the network structure is the *information* that various IMM participants obtain from each other and the entire market. Georg (2014) constructed an endogenous network using multi-agent simulations and showed that when banks received more informative signals about the world's underlying state, they valued liquidity coinsurance less than the threat of contagion via counterparty risk. In their simulation, as the signal's informativeness increased, the resulting network density decreased, and the network structure became sparser since banks feared counterparty risk. Fricke and Lux (2015) also justified the inclusion of large banks in the core of the Italian interbank network by arguing that large banks' comparative advantage in gathering and distributing information about their counterparts is considered a critical factor in hierarchical structures.

Banks' information about their counterparts' risk has also been reported in studies conducted by Blasques et al. (2018) and Castiglionesi and Navarro (2020). Both of them characterized optimal networks as core-periphery structures and argued that lenders more intensively monitor the big banks as the network money centers, and

they, in turn, closely monitor borrowers, leading to lower rates as well as fueling their role as market intermediaries. They found that when the counterparty risk is high enough, interconnections in a decentralized core-periphery interbank network may not be optimal, and network interconnections may be lost in some areas. The reason for this inefficiency is that the lending activity of a bank has a direct impact on the expected payoff of its neighbors in the IMM network. This network externality, in general, is not internalized, even if the transfer of bank capital is subject to an authorized lending decision.

(d) Self-restructuring

Another factor that scholars have not explicitly mentioned its impact on the formation of the IMM network, but can be identified through the literature in this field, is the ability of *self-restructuring* the network over time. Although scholars' views are sometimes contradictory, regardless of what these views are, they have recognized this factor in their research. By studying the interconnections among banks in the Italian overnight market, Iori et al. (2008) discovered a pattern of structural change in the network of many small creditors and a few large borrowers over the years and during the reserve maintenance periods with increasing network degree (i.e. the number of counterparts of each node) and decreasing strength for end-of-months. Also, Cajueiro et al. (2009)'s results suggested that the network fundamentals changed over time in Brazil.

In contrast, Fricke and Lux (2015) explored the network topology from a dataset of the Italian overnight transactions on the e-MID platform. They found that not only was the identified core relatively stable over time in terms of size and many other aspects, but there was also permanency over time in the position of banks as core or periphery members. Also, the results of applying a dynamic model to the time series of the daily overnight market in the UK by Giraitis et al. (2016) indicated that although some model parameters changed in response to the average reserves and events related to the 2007–2008 financial crisis, overall, the persistence of the IMM network increased over time. Agent-based simulations performed by T. Xu et al. (2016a) alleviated this

disagreement, showing that over time the structure of an IMM network evolves dynamically, but its topological properties remain unchanged. For instance, they found that as interbank lending risk preference increase, the average shortest path length became shorter, indicating improved network stability.

(e) Less Common Factors

As the last case identified across the IMM network literature, Chiu et al. (2020) showed that the *cost structure* to access the core of the market is crucial in explaining the IMM network's core-periphery structure. In their view, as one of IMM's realistic features, costly participation is based on evidence that cost-saving considerations force small banks to access the IMM through large correspondent banks. Their calibration also showed that it does not have to be expensive to produce the core-periphery structure. All of these findings are listed in Table 2.6.

Table 2.6. The factors affecting 'market structure'. The table lists the influencing factors on the market structure and the actors' strategies for these influences.

Affecting factor	Impact	IMM actors' strategies	Supporting literature
Liquidity: shock	Forward change	LB: Reduce their connections BB: Maintain connections by paying higher premium	(Squartini et al. 2013, Gabrieli and Georg 2014, in 't Veld and van Lelyveld 2014, Acemoglu et al. 2015, Fricke and Lux 2015, Vandermarliere et al. 2015, Pecora et al. 2016, T. Xu et al. 2016a, Affinito and Pozzolo 2017, Barucca and Lillo 2018, Blasques et al. 2018, Brassil and Nodari 2018, Kojaku et al. 2018, Brunetti et al. 2019)
Liquidity: injection	Backward change	BB: Mostly connect to the central bank to receive liquidity; reduce their other connections CB: Maintains network mode by managing market liquidity using the purchase or sale of securities	(Fique and Page 2013, Halaj and Kok 2015, Affinito and Pozzolo 2017, Barucca and Lillo 2018, Brunetti et al. 2019, Sümer and Özyıldırım 2019, Wegner 2019)

Bank characteristics	Formative	BB and LB: Connect to banks with more links, if new themselves; the larger they are, tend to more act as core; link with large banks, if small themselves, and vice versa; trade according to size	(Cajueiro and Tabak 2008, Cajueiro et al. 2009, De Masi 2009, Sokolov et al. 2012, Ben R. Craig and von Peter 2014, in 't Veld and van Lelyveld 2014, Lux 2015, T.C. Silva et al. 2016, A.J. Sun and Chan-Lau 2017, León et al. 2018, Sümer and Özyıldırım 2019)
Information	Forward change	LB: Monitor big banks; value counterparty risk more than premium; link with the banks whose expected gains are higher than their expected losses due to counterparty risk	(Georg 2014, Fricke and Lux 2015, Blasques et al. 2018, Castiglionesi and Navarro 2020)
Self-restructure	Formative	LB and LB: Increase their connections; maintain their position within the network	(Iori et al. 2008, Cajueiro et al. 2009, Fricke and Lux 2015, Giraitis et al. 2016, T. Xu et al. 2016a)
Market access cost	Formative	LB: link with large banks, if small themselves	(Chiu et al. 2020)

BB–borrower banks; LB–lender banks; CB–central bank

2.4.2.2 Relationship and Trust

In terms of the number of publications, the fourth primary IMM concern in this study is market participants' credit relationships, reflecting mutual trust among them (Temizsoy et al. 2015). However, in order to maintain the semantic coherence of the paper and provide a helpful building block before discussing macro-interdependences, such as systemic risk, contagion, and stability, we address this here. Nowadays, many unsecured interbank loans are verbally agreed upon and granted to partners through repeated loans (Renard 2017). Establishing more lending relationships in IMM provides borrowers with more diverse sources of liquidity (Ben R. Craig et al. 2015). Credit relationships, which enable banks with an enormous imbalance in their reserve deposits to borrow at a lower interest rate from banks with whom they have a relationship (Cocco et al. 2009), dynamically change due to the short-term nature of unsecured funding in the IMM (Anand et al. 2012). It means that loans continually mature and are established among both new and existing counterparts. Due to maintaining credit relationships, keeping the level of trust constant is vital for all market

participants, as its evaporation can lead to information asymmetry (Boot and Thakor 2000, Bräuning and Fecht 2017), market instability (Temizsoy et al. 2015, T. Xu et al. 2016a), and ultimately liquidity crises (Heider et al. 2009, Acharya and Merrouche 2013).

(a) Shock and Crisis

Shock to market or, more seriously, a *financial crisis* is the most frequent factor that scholars have addressed in relationship lending. A substantial number of publications suggest that banking crises have a positive impact on IMM credit relationships, meaning that the number and volume of relationship loans increase during the crisis (Cocco et al. 2009, Affinito 2012, Afonso et al. 2013, Bräuning and Fecht 2017, Orhun 2017, Renard 2017, Blasques et al. 2018, Degryse et al. 2019), while another group of publications explains a negative effect (Abbassi et al. 2015, Hatzopoulos et al. 2015, Temizsoy et al. 2015, Kobayashi and Takaguchi 2018, Liu et al. 2018).

Among the first attempts on the positive effect of shocks/crises, the study by Cocco et al. (2009) using Portuguese IMM data revealed that banks with more volatile liquidity shocks rely more on relationships and tend to borrow from banks facing fewer shocks. According to Affinito (2012), not only did the global financial crisis not stop lasting interbank relationships in Italy but also allowed lenders not to deprive their partners of interbank funds. In another study using US unsecured overnight data, Afonso et al. (2013) observed that when a liquidity shock occurs, borrowers with a higher liquidity deficit endogenously build concentrated relationships to protect their access to liquidity, while lenders provide preferential access to these borrowers. They argued that the *cost of searching* for the other side is a critical factor in maintaining existing relationships for both lenders and borrowers. Similarly, Bräuning and Fecht (2017)'s findings from a dataset of German unsecured overnight loans indicated that relationship lenders were more likely to offer liquidity to their closest borrowers in times of crisis. Therefore, borrowers earned liquidity at a lower rate from their relationship lenders. The robustness of similar relationships in credit line contracts under the circumstance that liquidity shocks were imperfectly, negatively correlated,

was also theoretically proven by Orhun (2017). In another study, Renard (2017) argued that relationships are especially relevant in crisis times as much confidence can be gained, and therefore, relationship loans are preferred to transactional loans when borrowers are distressed. Furthermore, Blasques et al. (2018) claimed that bank pairs that face low uncertainty about bank-to-bank credit risk maintain their lending relationships in times of crisis, leading to a decrease in the average interest rate spread of loans. Recently, Degryse et al. (2019) used contract data on the Russian overnight IMM to measure relationship strength between banks by the frequency and reciprocity of their daily interactions and affirmed that bank couples with ex-ante stronger relationships lend to each other more quickly and at lower interest rates in times of crisis than when contracting with other non-related banks and in non-crisis periods.

In the second strand, Abbassi et al. (2015) sought to identify, through European interbank data, how relationship lending and the supply of liquidity change throughout the crisis and before and after the main non-standard monetary policy shocks. Unlike the results obtained by the scholars of the first group, they concluded that the price dispersion exploited from different lenders on overnight uncollateralized loans increases massively with the crisis, so that relationship lenders charge higher prices for identical contracts, even more for riskier borrowers, and previous strong lending relationships do not help in this situation in general. In Italy, Hatzopoulos et al. (2015) showed that although preferential transactions are observed during the crisis period, and trading connections typically involve large trading volumes; the number of pairs of banks that perform preferential transactions decreases, and transactions occur at a higher interest rate than before the crisis. They confirmed that the trust-worthy relationships relatively increase during crisis periods, while some of the untrustworthy ones disappear. In two other studies on the Italian IMM data, both Liberati et al. (2015) and Temizsoy et al. (2015) found that although relationship lenders played an essential role as liquidity providers, especially amid the global financial crisis of 2007–2008, they nevertheless forced borrowers to pay premiums for transactions. A recent study on the Italian interbank network by Kobayashi and Takaguchi (2018) confirmed that relationship lenders tend to impose higher interest rates on borrowers in times of financial distress.

(b) History of the Relationship

The *history of interbank relationships* is another factor whose impact on trust between banks was examined for the first time by Affinito (2012) through analyzing the Italian IMM data. The author found that borrowers in Italy had been selected based on their pre-existing relationships during the global financial crisis. In a network simulation using a similar dataset, Iori et al. (2015) specifically emphasized the importance of lenders' memory (i.e. a history of relationships with borrowers) in their lending decisions. They showed that a lender, who has lent to a borrower many times in the past, is more likely to lend more quickly in the future than other borrowers who they have not or rarely have interacted with. Furthermore, Temizsoy et al. (2015) confirmed that a borrower who has been exposed to a lender benefits from access to more volume of overnight loans for a long time.

Examining the data recorded in the e-MID platform before and after the financial crisis, Finger and Lux (2017) found that the effect of past transactions plays a crucial role in sustaining many aspects of banks' behavior in managing their lending relationships during the crisis. This was also considered by Kobayashi and Takaguchi (2018) when defining 'significant tie' as a situation in which the number of trades between banks is too large to be explained by random chance. They applied a statistical test to the dataset of Italian overnight transactions and found that significant ties last longer than non-significant ties, which is in line with the conventional notion of relationship lending. The fact that banks tend to keep existing relationships has also been taken into account by Liu et al. (2018) in their IMM simulations. They modeled banks as passive learning agents who may learn to select better counterparts by evaluating their pre-existing relationships and updating relationship scores.

(c) Information

Affinito (2012)'s finding on the lack of ratings or having good ratings by banks (i.e. there is no bad news) refer to another important factor that affects their confidence in the market, i.e. the *information* that is officially or unofficially published about the status

of banks' balance sheets. Anand et al. (2012) used global game models to examine the effects of leaked information about market members on their confidence. They argued that the endogenous rate of collapse of a bank's lending relationship could be determined by the rate at which bad news about that bank's creditworthiness reaches, plus the maturity structure of its debt contracts. According to their observation, when market participants had imperfect common knowledge of fundamentals, the arrival of bad news about a borrower's balance sheet caused mistrust across all lenders, leading to a mass withdrawal of lending that forced the borrower bank into early liquidation. In another study, Marzo and Zagaglia (2014) concluded through a dataset of Reuters quotes on unsecured term loans (i.e. 1, 3, 6, and 12 months of maturity) that the likelihood of finding a trading counterpart with more in-depth information has increased since the turmoil in August 2007, as banks' reputation is an essential factor in choosing the trading counterpart. Also, Ben R. Craig et al. (2015)'s observation from Germany suggested that the private information available to lenders plays a vital role in the allocation of liquidity and the price paid by banks to meet their liquidity needs. Furthermore, Renard (2017) tried to model uncertainty using ambiguity and risk measures to find out how trustworthy IMM participants should be in order to be lent to by other participants. The author stated that since the effectiveness of engaging in a relationship depends on whether it allows lenders to adequately assess the worst-case scenario of borrowers' risk profile, for extreme ambiguity, the improvement in lenders' confidence via relationships will be too low.

(d) Banks' Size

A number of scholars have cited the *size of banks* as a factor influencing the relationship between banks. Cocco et al. (2009) showed that small banks and banks with a higher proportion of non-performing loans tend to rely more on relationships when borrowing money in the IMM. Also, Affinito (2012) found that when small borrowers are not rated or have a good rating, the lifespan of interbank relationships is longer. In another work, Sokolov et al. (2012) found that larger banks in the Australian IMM were more inclined to sustain more massive loan flows, as expected. Furthermore, Fricke and Lux (2015) concluded that core banks, mainly large banks, tend to rely on

periphery banks as an essential source of funding in times of distress because other core banks are less willing to provide liquidity than in regular times.

(e) Less Common Factors

The last factor affecting trust and interbank relationships that we found in this survey is *debt maturity*. The results of Anand et al. (2012)'s simulation, as mentioned above, revealed that dependence on debt maturity occurs only in combination with the default. They stated that in equilibrium, the credit amount decreases as debt maturity increases, and in the case of further increase, it will lead to the termination of the relationship. On the contrary, Temizsoy et al. (2015) discovered that long-term maturity trading between Italian banks increases the tendency to establish relationships and is positively correlated to the loan amounts. All of these findings are summarized in Table 2.7.

Table 2.7. The factors affecting ‘relationship and trust’. The table lists the influencing factors on the relationship and trust between banks and the actors’ strategies for these influences.

Affecting factor	Impact	IMM actors’ strategies	Supporting literature
Shock and crisis	Positive	BB: Build concentrated relationships with lenders; borrow more from partners facing fewer shocks LB: Provide preferential access to borrowers; offer more to closest partners; gain much confidence; lend to partners more quickly and at lower rates	(Cocco et al. 2009, Affinito 2012, Afonso et al. 2013, Bräuning and Fecht 2017, Orhun 2017, Renard 2017, Blasques et al. 2018, Degryse et al. 2019)
	Negative	BB: Pay higher rates to partners; borrow larger amounts LB: Impose higher rates on riskier partners; force partners to pay premiums CB: Performs non-standard monetary policy action	(Abbassi et al. 2015, Hatzopoulos et al. 2015, Liberati et al. 2015, Temizsoy et al. 2015, Kobayashi and Takaguchi 2018, Liu et al. 2018)

History of the relation	Positive	BB: Borrow from a partner for a long time; evaluate pre-existing relationships; keep existing relationships LB: Lend to a pre-existing partner; evaluate pre-existing relationships; keep existing relationships	(Affinito 2012, Iori et al. 2015, Temizsoy et al. 2015, Finger and Lux 2017, Kobayashi and Takaguchi 2018, Liu et al. 2018)
Information	Positive	BB: Have an easy-to-read balance sheet LB: Seek partners with more in-depth information; assess the worst-case scenario of a partner; foreclose the loan to a partner with bad news CB: Reduces disclosure requirements	(Affinito 2012, Anand et al. 2012, Marzo and Zagaglia 2014, Ben R. Craig et al. 2015, Renard 2017)
Bank size	Negative	BB: Borrow from larger banks, if small themselves, and vice versa; improve the rating if small LB: Seek small banks with not bad ratings	(Cocco et al. 2009, Affinito 2012, Sokolov et al. 2012, Fricke and Lux 2015)
Debt maturity profile	Negative	LB: Foreclose long-term loans (when receiving bad news) CB: Provides liquidity through long-term OMOs	(Anand et al. 2012)
	Positive	BB: Propose longer periods for higher amounts	(Temizsoy et al. 2015)
Counterparty search cost	Positive	BB and LB: Maintain existing relationships	(Afonso et al. 2013)

BB–borrower banks; LB–lender banks; CB–central bank

2.4.2.3 Default and Failure

The third concern that we surveyed in the IMM (the last one in terms of the number of publications) is that default means failure in repayment of the debt, including interest and principal on loans or securities. According to Eisenberg and Noe (2001), it is detected by examining whether the value of the liquid assets is less than the total nominal short-term liabilities. Consequences of default in a bank, if not controlled, can create new defaults in other market members, which will lead to higher interest rates

(Akram and Christophersen 2017) and ultimately drying up the market (Memmel et al. 2012, Memmel and Sachs 2013).

(a) Contagion and Systemic Risk

The most common influencing factor addressed by researchers in the field of default within the IMM is *contagion/systemic risk*. Contagion, as a chain of loss transmission, is not only a consequence of the failure of the previous node in the network, but also a factor for the failure of the next node. In modeling the distribution of losses in the Chinese IMM, Li et al. (2015) considered the risk of contagion throughout the market as the leading cause of cascading defaults to arbitrary banks. Li and He (2016) maintained this point of view in analyzing the impact of default probability on the loss distribution of defaults in IMM. Moreover, several studies identifying the set of defaulted banks during a clearing process implicitly addressed the significant role of contagion in default spreads (Rogers and Veraart 2013, Houy et al. 2019, Kusnetsov and Veraart 2019), although they focused only on stylized principles of insolvency law (Eisenberg and Noe 2001). They all suggested that the higher contagion risk increases the likelihood of new defaults in the network. This is why systemic important banks sometimes benefit from possible implicit government guarantees against default (Bernard and Bisignano 2000, Lucas and McDonald 2006, Atkeson et al. 2019, Nagel and Purnanandam 2020), meaning that they face relatively lower rates than their peers. This factor and its origins are reviewed in detail in Section 2.4.2.4.

(b) Capital Requirement

A key proposal put forward in Basel III requires banks to hold a higher percentage of *capital* relative to their risky assets. Accordingly, capital is the second most common factor, whose impact on banks' defaults has been studied by many scholars. This includes both capital requirements (e.g. leverage ratio and capital adequacy ratio), which should be set aside by banks to cover unexpected losses and keep themselves solvent in the crisis, as well as capital buffers, which should be held by them to ensure the accumulation of sufficient capital in prosperous times, aiming at absorbing losses

in the crisis. In a study on determining the pro-cyclical behavior and increasing the German banks' leverage (i.e. assets exceed capital), Schmielewski (2012) concluded that banks that prefer higher leverages have a lower distance-of-default that indicates the vulnerability of such banks during the times of crisis. The author then provided some empirical evidence that regulatory authorities should consider requirements on counter-cyclical capital buffers in the context of macroeconomic indicators. The discovery of several underlying factors was one of the empirical findings of the US IMM study by Oet and Ong (2019), explaining the variance of interbank activity data across tiers. They showed that change in return and balance sheet growth was significantly related to interbank activity, and changes in liquidity and changes in leverage had a mediated relationship via growth and change in return.

To find the minimum capital adequacy ratio – as the first pillar of Basel – required for each bank to prevent contagious defaults in the banking system, Mitja Steinbacher and Steinbacher (2015)'s results revealed that larger banks with adequate capital are expected to default less than smaller, poorly capitalized banks and need lower additional capital to avoid bankruptcy when hit by a shock. Similarly, Barroso et al. (2016) demonstrated that setting a minimum requirement for banks' capital adequacy ratio has a significant role in reducing bank failure risk. As this ratio is obtained by dividing the tiers 1 and 2 capital on risk assets, it can be inferred that the higher the capital, the lower the risk of failure. The empirical simulation study developed by Capponi et al. (2017) to test mitigation policies targeting default resolution revealed that capital buffers reduce both the number of defaults and the resulting losses.

(c) Banks' Size

The next factor affecting the failure of banks in the market is their *size* based on the value of their total assets. Through a study on the intensity of default spreads in different interbank network topologies, Rogers and Veraart (2013) found that when net assets decrease, both the losses due to default and the proportion of defaulting banks increase. This is aligned with Mitja Steinbacher and Steinbacher (2015)'s results regarding the expectation that larger banks are less defaulting than smaller banks, as

mentioned above. Also, another finding of Capponi et al. (2017), in addition to what was mentioned before, was that the default mitigation effect increases (i.e. the probability of default decreases) as the fraction of assets resolved increases (i.e. the bank size increases). Recently, in quantitative research on the macro-prudential regulation for the Chinese IMM, Q. Gao and Fan (2020) concluded that bank size is the critical factor for banks' basic default. By analyzing each bank's capital changes, they stated that it is essential to allocate large banks' extra capital to small banks with high risk.

(d) Credit Spread

The interbank *credit spread*, as the difference in yield between treasury bills and other debt securities (used as collateral for loans) of the same maturity but different quality, is another factor whose positive correlation with the default risk is suggested in the pioneer study performed by Taylor and Williams (2009) on the effectiveness of Federal Reserve's policies during the recent financial crisis. A similar correlation was also expressed by J. Smith (2012) through a no-arbitrage model of the term structure of spreads during the financial crisis. Furthermore, Arias (2013) developed an empirical model of the IMM with endogenous defaults and showed that as the spread of credit increases in the IMM, so does the probability of banks' default. The author argued that there is no spread and zero default probability of banks in the market in standard times, but in times of crisis, an interbank credit spread arises endogenously, and some banks default.

(e) Less Common Factors

A review of the literature reveals that individual researchers have claimed several other factors in addition to those mentioned above. Simulations performed by Barroso et al. (2016) to examine the impacts of regulatory policies on the IMM revealed that higher *interest margins* (i.e. the difference between banks' cost of funding and their return from loans) in the IMM lead to a higher risk of bank failures. Sarmiento et al. (2017) developed an early-warning indicator system to identify those banks that were paying

higher *prices* for liquidity in the IMM as risky counterparts. In their experiment on the overnight unsecured data from the Colombian IMM, the share of signals from participants with a net borrower position was negatively correlated with the Z-score, which corresponds to the inverse probability of insolvency (Roy 1952, Altman 1968), meaning that a larger proportion of signals could be associated with a higher expectancy of insolvency (i.e. a lower Z-score). In a study to address the problem of systemic risk assessment in IMM networks where interbank liabilities can have multiple maturities, Kusnetsov and Veraart (2019) demonstrated that the risk of default of banks significantly depends on the detailed maturity profile of its liabilities. It means that when all maturities are the same, the number of banks that default is less than when maturity dates are different. Table 2.8 summarizes all of the findings mentioned above.

Table 2.8. The factors affecting ‘default and failure’. The table lists the influencing factors on banks’ failures and the actors’ strategies for these influences.

Affecting factor	Impact	IMM actors’ strategies	Supporting literature
Systemic risk	Positive	BB: Pay lower rates than others if systemically important CB: Grants guarantees to systemic important banks; prevents the spread by allowing the failure of some banks	(Rogers and Veraart 2013, Li et al. 2015, Li and He 2016, Houy et al. 2019, Kusnetsov and Veraart 2019)
Capital requirement	Negative	BB: Minimize the capital buffer; optimize leverage LB: Maximize the capital buffer CB: Sets minimum capital requirements; liquidates banks with an insufficient capital ratio	(Schmielewski 2012, Mitja Steinbacher and Steinbacher 2015, Barroso et al. 2016, Capponi et al. 2017, Oet and Ong 2019)
Bank size	Negative	BB: Sell risk assets at a discounted price at auction LB: Allocate extra capital to risky smaller banks, if large themselves	(Rogers and Veraart 2013, Mitja Steinbacher and Steinbacher 2015, Capponi et al. 2017, Q. Gao and Fan 2020)
Credit spread	Positive	LB: Lend against higher-quality securities CB: Performs non-standard monetary policy action	(Taylor and Williams 2009, J. Smith 2012, Arias 2013)

Interest margin	Positive	LB: Optimize the interest margin	(Barroso et al. 2016)
Loan price	Positive	CB: Monitors banks with a significant insolvency risk	(Sarmiento et al. 2017)
Debt maturity profile	Negative	BB: Borrow funds with the same maturity date CB: Applies appropriate clearing models	(Kusnetsov and Veraart 2019)

BB–borrower banks; LB–lender banks; CB–central bank

2.4.2.4 Contagion and Systemic Risk

Systemic risk, though it is a concept that has been used in the financial market literature since the 1980s (Cline 1984a, 1984b), seems to be intimately associated with the financial crisis of 2007–2008. Due to this view that the IMM is an environment that provides risk-sharing (i.e. liquidity coinsurance) among banks (Castiglionesi and Navarro 2020), by lending to each other, they build a network of interbank exposures that exposes other banks to potential failure. This theme, which researchers highly regarded in the last two decades, has the largest number of documents in our scientific repository. Publications related to all three primary forms of systemic risk distinguished by the ECB (i.e. the contagion risk, the risk of widespread exogenous shocks causing simultaneous problems, and the risk of the unraveling of the endogenous build-up of widespread imbalances over time) (ECB 2009, Constâncio 2010) are considered.

Of these three forms of systemic risk, ‘contagion’ seems to be the most common, for which, according to the literature in this field, several channels have been identified. As defined by ECB (2009),

“contagion usually refers to a supposedly idiosyncratic problem that becomes more widespread in the cross-sectional dimension, often in a sequential fashion.”

As observed in many cases; like Herstatt Bank in 1974, Northern Rock in 2007, and Lehman Brothers in 2008; when a bank is idiosyncratically shocked, and all of its assets are wiped out, this leads to the loss distribution among a network of interconnected banks that are somehow related to the failed bank. Suppose this

defaulted bank has borrowed from another bank in a network, and that bank, in turn, has received a loan from another bank, and so on. As a result of the first-round effects, only direct creditors of the initial defaulted bank are affected. If any other banks default due to the shock coming from that bank, this time, the banks lending to them would be affected through second-round effects. Because this cycle may continue in this way, leading to new rounds of effects, these different rounds form a series of contagion channels, called ‘direct effects’ (Mommel and Sachs 2013, Amini and Minca 2016, Siebenbrunner et al. 2017, Siebenbrunner 2020). Banks that are neither directly nor indirectly exposed do not suffer losses under this channel, which, according to our repository, is the most common channel of contagion in the IMM literature.

In the example above, suppose there are also several other banks in the network that have neither borrowed from nor lent to any of these banks but are indirectly connected to them through common asset holdings (i.e. overlapping portfolios). The second channel, ‘correlated losses,’ is related to the hold of correlated assets by banks so that a general macro shock would translate into a set of idiosyncratic shocks on each bank’s assets (Elsinger et al. 2006, Caccioli et al. 2015, Pollak and Guan 2017, Siebenbrunner 2020). ‘Fire-sale’ is another channel of contagion related to the liquidation of defaulted banks. Fire-sale losses reduce the recovery value of loans granted to defaulted banks, thereby increasing their creditors’ losses (Caccioli et al. 2015, Cimini and Serri 2016, Siebenbrunner et al. 2017, Siebenbrunner 2020). Furthermore, in a banking system that uses a ‘mark-to-market’ regime for the accounting of common assets, it is necessary to recognize the liquidation losses from depressed assets by all banks, even those that have not been exposed to the interbank network (Georgescu 2015, Siebenbrunner et al. 2017, Siebenbrunner 2020). This effect is also considered as another contagion channel. Since the last three channels are related to the notion of the ‘asset market’ in addition to the IMM (Aldasoro and Angeloni 2015, Siebenbrunner et al. 2017, Siebenbrunner 2020), they are out of the scope of our survey.

(a) Network Characteristics

According to many researchers, network structure has a significant impact on the probability of contagion, as the largest number of publications in this field is devoted to network characteristics. When the banking system is presented as a network, usually by removing some nodes (Bardoscia et al. 2015), i.e. when banks default (Nier et al. 2007, Upper 2011, Caccioli et al. 2012), if their balance sheets deteriorate (Martinez-Jaramillo et al. 2014, Amini et al. 2016) propagation of shocks occurs. This can also happen in combination with other contagious channels, such as those due to cash-flow insolvency (Cont and Minca 2016) or fire-sales and overlapping portfolios (Caccioli et al. 2015, Cimini and Serri 2016). Although no single topological structure is always the most robust due to many other factors, such as market liquidity (Roukny et al. 2013), its importance in terms of connectivity between financial institutions through balance sheet linkages is such that it is one of the critical factors proposed by the FSB (2009) and IMF (2010) in measuring the systemic importance of banks.

Although the size of the bank, which initially fails, is a significant factor in the occurrence of contagion, the structure of the lending network is crucial to the extent of spread (Krause and Giansante 2012). It also has significant consequences on the default cascade (Gonzalez-Avella et al. 2016), as it affects the effectiveness of banks' strategies to manage liquidity and overcome risks (Denbee et al. 2018). Publications that have addressed the impact of the network on systemic risk have focused primarily on connectivity and the central position of the contaminating bank in the network and the concentration, although documents on other network features can also be found.

Most researchers believe that there is a positive correlation between *connectivity* and systemic risk. From the theoretical view, Caccioli et al. (2012) focused on the impact of network topology on systemic risk and showed that although in scale-free networks, a series of failure cascades due to a random shock was less likely than in random networks, when a node with high connectivity was shocked, systemic risk in this structure was much higher. In this regard, Lenzu and Tedeschi (2012) found a threshold for connectivity between banks in a scale-free network, beyond which the probability of contagion was significantly increased. D. Yao et al. (2016) examined the contagion due to a bank's failure to its creditors and the whole system and showed that

if the source bank is highly interconnected, contagion effects are very significant. Simulations performed by Calimani et al. (2019) also suggested similar results. From the empirical point of view, results from the studies of the German IMM by Anand et al. (2015), the Kenyan IMM by Fan et al. (2018), the Chinese banking system by Lin (2018), the European payment system TARGET2 by Gabrieli and Salakhova (2019), and the Austrian IMM network by Diem et al. (2020) all confirmed that systemic risk positively depends on the level of interconnectedness in the interbank network. One possible reason for these findings could be that with more connectivity, there are more paths through which contagion can spread.

There are also opponents among researchers, who believe that further connectivity improves risk-sharing in the network and reduces the contagion risk. Contrary to what the first group of scholars illustrated, the estimates by Rünstler (2016) in the Euro area interbank network during the European financial crisis as well as investigations by T.Y.H. Nguyen (2018) using empirical data of the UK's IMM suggested that network linkages mitigated idiosyncratic shocks across the network rather than amplifying them, as defaulting nodes' neighbors could have partly absorbed shocks. Similarly, Duffy et al. (2019) pointed out that more complete interbank network structures can reduce financial contagion incidence. Furthermore, simulations by Li et al. (2019) yielded similar results in multiplex networks. They found that the systemic risk decreased with increasing the average degree (i.e. the number of links compared to the number of nodes) of the two layers and more decreased under the two layers' average degrees. Gaffeo et al. (2019)'s viewpoint was more moderate than those of the scholars mentioned so far. They identified a non-linear relationship between connectivity and contagious defaults. Studies by Walters et al. (2019) revealed that connectivity, combined with other network characteristics, potentially affects the system's strengthening or weakening through the network's tiering level. Also, Simaan et al. (2020), who considered IMM as a money supply chain, stated that the less the connectivity between clusters and the more the connectivity within clusters in the network is, the more serious the network would be threatened.

There is an idea that an interconnected bank's systemic risk depends not only on the expected loss it imposes directly on depositors but also on its position in the IMM network (Puhr et al. 2012, Lin 2018). Accordingly, the first defaulted node's *central position* in the network is the next frequent attribute that affects the systemic risk. Pioneering research into the evolution and determinants of contagion risk for the Belgian banking system by Degryse and Nguyen (2007) revealed that the shift from a complete structure (where all banks were symmetrically linked) to a multicores-periphery structure (where the core banks were connected to each other and to periphery banks) reduced the risk of contagion. According to simulation-based, comparative analysis between different types of network structures performed by Lee (2013), a core-periphery network with a deficit money center bank creates the highest systemic risk level. Moreover, applying a dataset extracted from e-MID, Roukny et al. (2013) observed that hubs in any network increase the chance of contagion between various parts of that network. Later, the results of analyzing the probability of cascades in the same market by Karimi and Raddant (2016) confirmed that the centrality and coreness of the initial defaulter within the network play an essential role in its ability to start a cascade. Recently, Ferrara et al. (2019) studied systemic illiquidity in UK banks using a dataset including the short-term interbank funding transactions and found that banks' position in the IMM network is an essential determinant for calculating the systemic importance of banks.

According to the literature, network *concentration*, as a proxy for competition between banks, is another influential systemic risk factor. A network model of interbank lending developed by Gai et al. (2011), including both secured and unsecured loans, illustrated that greater concentration in the IMM network might amplify the contagion. Using e-MID data, Roukny et al. (2013) examined several benchmark topologies in a simple default dynamics. They found that scale-free networks characterized by a higher level of heterogeneity in the number of financial linkages were riskier than regular and random networks due to the stronger market concentration, which causes some nodes to become centers for shock propagation. Another possible reason is that when a concentrated market is illiquid, a much larger number of borrowers exposes the hubs to a larger number of defaults, which increases

the likelihood of default for this small number of creditors. Similarly, Fei et al. (2015) found that the bank with the highest concentration degree in the US induces a mild contagion. In another work, Berardi and Tedeschi (2017) studied the impact of low interest rates and high liquidity supply strategies on different network topologies' fragility. They found that the system vulnerability was strongly related to the network concentration, meaning that when there were very few hubs acting as lenders, the high leverage (i.e. the low capital held against the exposure) was often associated with high failures. This is completely aligned with Roukny et al. (2013)'s findings. Ben R Craig and Ma (2018) demonstrated that in the German IMM, where a few large banks intermediate funding flows between many smaller periphery banks, shocks to large banks in times of financial crisis are transmitted to periphery banks through intermediate networks, and this provides a vital source of systematic risk. Recently, Zedda and Sbaraglia (2020) concluded that low concentration levels (i.e. high diversification) keep the system less prone to contagion, while higher concentration can progressively enhance contagion.

From another point of view, interbank loans expose the balance sheet of banks by bookkeeping the value of loans in creditors' assets and debtors' liabilities. The *number and size of exposures* (i.e. the total amount of interbank lending transactions that a bank conducts with other financial institutions) in any weighted banking network – where not all ties have the same capacity – is considered by scientists to be one of the factors influencing contagion and systemic risk. Li and He (2012), who examined the impact of banking activities on contagion risk in various types of interbank network structures, identified the size of interbank exposures as a significant factor in determining the impact of contagion risk. What they meant was that increases in the size of interbank exposures might increase the threat of contagion risk in small-world networks, followed by tiered, random, and scale-free networks, respectively. Besides, the degree of equality in the distribution of interbank exposures was considered by Memmel and Sachs (2013) as an essential determinant for predicting the expected number of failures in the German IMM network to find out how equal banks spread their claims among other banks. In another work to understand the impact of counterparty failure on the entire banking system's stability, Birch and Aste (2014)

studied a stylized banking model based on balance sheet values. They demonstrated that although interbank exposure can increase the stability (see Section 0), this is at the cost of increasing the risk of sudden systemic failure. Recently, Li et al. (2019) stated that in most cases, the systemic risk increases with the increase in the lending scale and that

“only the long-term effect of systemic risk has a negative correlation with the short-term lending scale.”

The last feature of the network affecting systemic risk is *entropy*, which refers to the relative degree of randomness and measures the distribution of interbank exposures within the system. By constructing artificial banking systems, He and Li (2017) investigated the three kinds of potential interbank networks (i.e. random, small-world, and scale-free topologies) and found that network entropy is positively correlated with the effect of systemic risk on all three types of interbank networks.

(b) Banks' Size

In our survey, the size of market players, which is usually calculated based on the value of *total assets*, is the second most important factor, after the network, influencing contagion and systemic risk in terms of the number of publications, which many researchers have addressed both empirically and theoretically. From the empirical point of view, Toivanen (2009), in estimating the danger of contagion in the Finnish IMM, found that banks' size was a critical factor in occurring cascades and that medium-sized banks, in addition to large commercial banks, could also have caused some destructive domino effects. Very similar results for the Italian IMM was achieved by Battiston et al. (2013). In Germany, Memmel and Sachs (2013) performed simulations to show that the share of interbank assets relative to total assets is an essential determinant of the expected number of failures in the network. In Europe, stress test exercises by Battiston et al. (2016) and the network model developed by Aldasoro et al. (2017) suggested that institutions that were both vulnerable and influential (as the two main variables for measuring systemic risk) were generally large in terms of asset size. Also, two results of the Chinese IMM network's stress test by X.

Gao et al. (2017) was that the size of banks was crucial to their systemic importance and that the network contagion effect could significantly have changed the elasticity of banks' systemic importance concerning their size. These results were reached again in Q. Gao and Fan (2020)'s study.

From the theoretical point of view, in a comparison of the 'too-big-to-fail' vs. the 'too-interconnected-to-fail' ideas through comparing the probability of a conditional failure of the most connected versus the largest bank, Caccioli et al. (2012) discovered that while networks with a low average degree were more affected by highly connected banks, large banks' failure had more impacts on networks with a high average degree. Kanno (2015) also used the estimated bilateral exposures matrix to demonstrate that in an IMM characterized by a power law in the distribution of contract sizes, when a large bank in the core of the network initially defaults, it becomes a source of contagion. Besides, Smerlak et al. (2015) analyzed the risk contagion characteristics of a single bank and found that large and low-capital banks increase systemic risk in the network. Models developed by Calimani et al. (2019) and Gaffeo et al. (2019) to investigate the risk of contagion in the network suggested that a system with larger nodes is more prone to contagion risk stemming from funding shocks. In another study, Li et al. (2019) constructed a multiplex network model of banks with arbitrary structure and by doing numerical simulation, found that with the increase of the proportion of the net worth of banks (i.e. their total assets minus their total liabilities), the systemic risk effect shows a non-linear decreasing trend. According to the above literature and as recently found by Zedda and Sbaraglia (2020), small banks' lending to larger, riskier banks is the most threatening to the system's stability.

According to the literature, another factor that plays a vital role in shock transmission across the network is the *heterogeneity* among banks in size, credit, etc. In a heterogeneous system where contagion occurs due to a large bank's failure, it seems that exposure for its creditors will undoubtedly lead to a worse situation than when banks are homogeneous (Iori et al. 2006, Lenzu and Tedeschi 2012). A pioneering attempt by Iori and Jafarey (2001) revealed that as long as banks are similar in size and exposure to risk, the effects of cascading failures are small, but as the heterogeneity

increases, these effects become more important. They showed that by varying the heterogeneity among banks, the system enters a critical regime with a power-law distribution of cascade sizes. Li and He (2012) also found that the effect of contagion risk in networks with heterogeneous banks is more substantial than that among homogeneous banks, and there is a positive correlation between the effect of contagion risk and heterogeneity of banks. Recently, by developing an agent-based model and using real data from the stress test in Europe, Halaj (2018) found that the contagion drivers depended on the agents' heterogeneity in the financial system.

(c) Capital Requirement

Market members' *capital requirement* is another factor that many scholars in the last decade have studied its effects on contagion and systemic risk. Theoretically, Choi (2012) showed that systemic risk critically depends on the level of leverage of institutions in the contagion chain, as the financial health of stronger (lower leveraged) institutions is very crucial. However, financial contagion originates in weaker (higher leveraged) institutions. Similarly, D. Yao et al. (2016) found that contagion effects are most significant if the originating defaulted bank is highly leveraged. Accordingly, Gurgone and Iori (2019) focused on macro-prudential capital requirements, and by testing several simulation scenarios, they showed how capital requirements could mitigate systemic risk. In this regard, Gaffeo et al. (2019) and Leventides et al. (2019), like other researchers, identified an inverse relationship between the capitalization level imposed on banks and financial contagion.

According to the reviewed literature, quite similar results were obtained in empirical studies. A study of bilateral exposures in the Italian IMM by Battiston et al. (2013) suggested that the effect of a bank's capital on the systemic risk is much higher when the network is tightly interconnected. Also, Memmel and Sachs (2013) applied banks' capital ratio as an essential determinant of the expected number of failures in their contagion simulations for the German IMM network. In comparing the contagion risk in the IMM between China and the US, Fei et al. (2015) found that a group of banks with the lowest capital adequacy ratio in China caused a serious

contagion due to the over-activity of most banks in the Chinese IMM. Furthermore, Souza et al. (2015), using a dataset from the Brazilian financial system, showed that low capital buffer levels are worrisome, as they are associated with greater vulnerability and may significantly increase losses. Moreover, Wolski and van de Leur (2016) found that a higher leverage allowance increased the German IMM's bankruptcy rate. In another study using UK IMM data, T.Y.H. Nguyen (2018) found that increasing the capital ratio decreases the fraction of default, especially at higher shock levels.

Contrarily, Calimani et al. (2019) believed that higher bank capital requirements might exacerbate contagion by motivating banks to increase exposures in the IMM, leading to lower capital buffer levels above the minimum requirement. They argued that banks with higher levels of capital initially

“have an incentive to keep less risky assets, i.e. the interbank lending, which does not require holding as much capital as riskier assets, i.e. the less-liquid assets. However, this leads to an excess supply of interbank claims and drives down the risk-free return rate of bank lending that, as a consequence, becomes a less attractive investment for banks. The higher capital also means a lower default probability and, consequently, lower funding costs. Hence, there is a trade-off. On the one hand, the increase in the capital requirement lowers the total volume of the interbank lending market. On the other hand, the lower risk-free rate and lower default probability imply lower interbank borrowing costs. Consequently, banks want to borrow more money to invest in the riskier assets, increasing homogenization of asset allocation, and the fire-sale losses following liquidity shocks are more pronounced.”

(d) Liquidity Requirement

An appropriate *liquidity requirement* (i.e. the fraction of banks' deposits they must hold in cash) is another crucial factor affecting contagion and systemic risk, as liquidity deficit can lead to more illiquidity-driven default cascades. Under Basel III, banks must tighten the minimum reserve ratios that would force them to hold a higher proportion of liquid reserves, providing them with increased protection against liquidity shocks. Using simulation experiments, Li and He (2012) showed that increasing the size of liquid assets can reduce the risk of contagion across all types of IMM networks. Furthermore, network analysis and quantifying the negative externality cost that arises with illiquidity-driven defaults by Gaffeo and Molinari (2015) confirmed liquidity requirement as a mechanism to force banks to internalize the cost of sudden liquidity

shocks that would otherwise amplify contagion spread. They stated that liquidity reserves could completely internalize the negative financial externality resulting from illiquidity-driven default and reduce contagion dynamics. Also, in order to study the trade-off between the mitigation of systemic risk, Aldasoro et al. (2017) developed a network model of the IMM and demonstrated that an increase in the liquidity requirement reduces systemic risk more sharply and more rapidly than an increase in equity requirements, but with less efficiency. More recently, Halaj (2018) confirmed that liquidity requirements are useful instruments to mitigate contagion risk.

(e) Cross-border Relationship

According to the literature, another factor influencing the spread of contagion in an IMM is the *cross-border lending relationship* with foreign IMM, which is achieved through foreign bank branches in one country's market or the presence of that country's bank branches in foreign markets. van Lelyveld and Liedorp (2006) believed that the most critical risks in the Dutch interbank market were due to exposure to foreign counterparts. Because many banks were exposed to foreign regions, all types of banks would be severely affected if problems arose in one of these regions. The authors left a careful assessment of these effects to future research. Degryse and Nguyen (2007) argued that, on the one hand, the increased cross-border interbank exposures by Belgian banks reduced local contagion risk, and on the other hand, contagion risk due to the default of large foreign banks in the Belgian market might have increased. Although they attributed 85% of the default in the Belgian market to foreign banks' activity, they did not point out that, given the reduced risk of Belgian banks operating in foreign markets, the overall effect of cross-country activity on the contagion was positive or negative. More recently, Gabrieli and Salakhova (2019) examined the scope for cross-border contagion in Europe using TARGET2 payment data and claimed that despite the high level of cross-country interconnections, domestic losses are still more critical than cross-border losses in many countries.

In contrast to the above studies, another group of researchers emphasizes the effective role of cross-border relationships among the interbank network in increasing

systemic risk. Another study on the foreign banks' activity in the Dutch IMM by Liedorp et al. (2010) indicated a positive relationship with contagion in the market. Similarly, Halaj (2018) found evidence of an active cross-border channel of contagion in Europe with damages from one country to another. One of the main reasons for this effect seems to be that cross-border relationships play a critical role in regulatory arbitrage and restrict domestic regulators' ability to limit bank risk-taking, as jurisdiction regulators typically cannot evaluate counterparty quality due to limited transparency (Houston et al. 2012, Karolyi and Taboada 2015).

(f) Information

According to the publications in our repository, *information* and the level of access to it, along with informative transparency and information symmetry, represent another factor influencing the increase or decrease of systemic risk in the IMM. Asymmetry in access to counterparty information for market members is a factor that increases the systemic risk within the market, while the lack of information on loan transaction details for market analysts and stress testers in central banks leads to inaccurate estimates of the risk. Numerous discontents from researchers with the confidentiality of access and the lack of accurate information on interbank loans, which forces them to deduce this information from banks' balance sheets, payment systems transactions, etc., reveal how important it is to have information on bilateral positions. Many researchers believe that the aggregate data that is typically available does not allow them to take into account the actual structure of the interbank network, which can lead to substantial errors in measuring systemic risk (Upper and Worms 2004, Degryse and Nguyen 2007, Upper 2011, Drehmann and Tarashev 2014, Zedda et al. 2014, Anand et al. 2015, Andreucut 2016).

Researchers working on the subject of information have identified it as an essential factor in reducing systemic risk. Thurner and Poledna (2013), using an agent-based model, demonstrated that by increasing market transparency by making the systemic importance score of single banks visible to all banks, and by applying a simple incentive scheme, which leads to the reduction of interbank borrowing from systemically risky

banks, systemic risk in the IMM network could be significantly reduced. By simulating an interbank clearinghouse acting as a central counterparty, Barroso et al. (2016) showed that the two main tasks of such a system, including the use of collateral and information disclosure from market participants, were successful in reducing the risk of contagion between banks. Also, by constructing a duplex network model and by doing a simulation experiment to investigate the transmission mechanism of systemic risk in a banking system, Ding et al. (2017) found that asymmetric interaction of information increases the inflexibility of the system, which leads to a lack of liquidity and possibly the collapse of the entire market. Examining the transmission mechanism of shock in the network, they argued that the accumulation of risk resulting from information asymmetry was a major contributing factor to systematic risk.

(g) Less Common Factors

Other factors influencing systemic risk that we have explored in the literature include *collateral*, *shock characteristics*, and *interest rate*. On the subject of collaterals received by banks against the loans they grant in the IMM, as mentioned above, Barroso et al. (2016) found it useful in mitigating the network's risk of contagion. In addition, simulations by Wolski and van de Leur (2016) indicated that the decline in collateral quality is reflected in higher interbank rates as well as the increased riskiness of the banking sector, while the effects of improving collateral quality are negligible. One possible reason for the impact of high-quality collateral on reducing systemic risk could be that adverse shocks change banks' preferences towards safer assets. Because not all banks can use quality collateral as a cheap source of liquidity, they are less involved in interbank transactions and therefore maintain higher capital buffers, which reduces the number of bankruptcies. This is in line with the findings of Gorton and Metrick (2012) and Krishnamurthy et al. (2014) who found that banks with a large share of lower-quality securities in repo collateral were more vulnerable during the subprime crisis of 2007.

In connection with Shock, Borovykh et al. (2018), using a mean-field model of interacting diffusions for monetary reserves subjected to self- and cross-exciting

shocks, demonstrated that self-exciting shocks (i.e. financial acceleration due to the dependence of current variations in the asset side of the balance sheet on past variations in the assets themselves) increase systematic risk in the network. Also, Halaj (2018) illustrated that the relationship between funding shocks and contagion losses is nonlinear and exhibits cliff effects. Apropos of interest rate, Berardi and Tedeschi (2017) argued that when a lender lends to an over-leveraged borrower, it imposes higher interest rates through the financial accelerator, which in turn worsens the borrower's financial condition. When several borrowers are unable to pay off, lenders also reduce their credit supply and increase borrowers' rationing. In this way, the borrowers' profit margins are reduced, and a new round of failures may occur. All of the above findings are listed in Table 2.9.

Table 2.9. The factors affecting 'contagion and systemic risk'. The table lists the influencing factors on contagion and systemic risk and the actors' strategies for these influences.

Affecting factor	Impact	IMM actors' strategies	Supporting literature
Network: connectivity	Positive	BB: Prefer to borrow from well-connected banks, if less-connected themselves , and vice versa LB: Prefer to lend to well-connected banks, if less-connected themselves , and vice versa	(Caccioli et al. 2012, Lenzu and Tedeschi 2012, Anand et al. 2015, D. Yao et al. 2016, Fan et al. 2018, Lin 2018, Calimani et al. 2019, Gabrieli and Salakhova 2019, Gaffeo et al. 2019, Walters et al. 2019, Diem et al. 2020, Simaan et al. 2020)
	Negative	Similar to the positive effect	(Rünstler 2016, T.Y.H. Nguyen 2018, Duffy et al. 2019, Gaffeo et al. 2019, Li et al. 2019, Walters et al. 2019, Simaan et al. 2020)
Network: centrality	Positive	BB and LB: Become more central as they are larger; more tighten with important counterparts CB: Considers core banks more important in a systemic sense	(Degryse and Nguyen 2007, Puhr et al. 2012, Lee 2013, Roukny et al. 2013, Karimi and Raddant 2016, Lin 2018, Ferrara et al. 2019)
Network: concentration	Positive	BB: Hunt lenders offering interest rate increasingly lower in a concentrated market; highly leverage when there are very few lenders; diversify portfolio	(Gai et al. 2011, Roukny et al. 2013, Fei et al. 2015, Berardi and Tedeschi 2017, Ben R Craig and Ma 2018, Zedda and Sbaraglia 2020)

Network: number & size of exposures	Positive	BB: Optimize portfolio based on the cost of borrowing LB: Optimize portfolio based on the returns on money lending	(Li and He 2012, Memmel and Sachs 2013, Birch and Aste 2014, Li et al. 2019)
Network: entropy	Positive	BB and LB: Diversify losses as much as possible	(He and Li 2017)
Bank size: total assets	Positive	BB: Prefer to borrow from large banks, if small themselves , and vice versa LB: Diversify assets; prefer to lend large amounts to large banks, if small themselves , and vice versa	(Toivanen 2009, Caccioli et al. 2012, Battiston et al. 2013, Mommel and Sachs 2013, Kanno 2015, Smerlak et al. 2015, Battiston et al. 2016, Aldasoro et al. 2017, X. Gao et al. 2017, Calimani et al. 2019, Gaffeo et al. 2019, Li et al. 2019, Q. Gao and Fan 2020, Zedda and Sbaraglia 2020)
Bank size: heterogeneity	Positive	BB: Borrow from large banks, if small themselves , and vice versa LB: Lend to large banks, if small themselves , and vice versa	(Iori and Jafarey 2001, Iori et al. 2006, Lenzu and Tedeschi 2012, Li and He 2012, Halaj 2018)
Capital requirement	Negative	BB: Leverage up to the regulatory minimum	(Choi 2012, Battiston et al. 2013, Memmel and Sachs 2013, Fei et al. 2015, Souza et al. 2015, Wolski and van de Leur 2016, D. Yao et al. 2016, T.Y.H. Nguyen 2018, Gaffeo et al. 2019, Gurgone and Iori 2019, Leventides et al. 2019)
	Positive	BB: Leverage up to the regulatory minimum LB: Keep less risky assets	(Calimani et al. 2019)
Liquidity requirement	Negative	BB and LB: Estimate the net cash flow; hold minimum liquid assets BB: Deleverage or sell non-liquid assets LB: Get liquidity back from more sources CB: pays interest on banks' reserve	(Li and He 2012, Gaffeo and Molinari 2015, Aldasoro et al. 2017, Halaj 2018)
Cross-border relation	Positive	BB: Borrow more from foreign banks than domestic banks LB: Lend more to foreign banks than domestic banks	(Liedorp et al. 2010, Halaj 2018)

	Unclear	BB and LB: Became better capitalized	(van Lelyveld and Liedorp 2006, Degryse and Nguyen 2007, Gabrieli and Salakhova 2019)
Information	Negative	CB: Imposes information disclosure to banks; maintains clearinghouse	(Thurner and Poledna 2013, Barroso et al. 2016, Ding et al. 2017)
Collateral	Negative	BB: Provide collateral proportional to the loan size CB: Collects collateral from IMM participants	(Barroso et al. 2016, Wolski and van de Leur 2016)
Shock characteristics	Positive	BB and LB: Absorb shocks by net worth (capital); transfer the shock residual to the connected banks	(Borovykh et al. 2018, Halaj 2018)
Interest rate	Positive	LB: Offer the best condition in terms of interest rate	(Berardi and Tedeschi 2017)

BB–borrower banks; LB–lender banks; CB–central bank

2.4.2.5 Stability

The recent literature on the two themes of systemic risk and stability is strangely intertwined. In general, financial market stability means

“the absence of the kind of volatility that could have several real economic consequences”

and

“is most often thought of in terms of avoiding financial crises ... and also ... in terms of managing systemic financial risk” (Schinasi 2003).

The only tactic we have used to distinguish literature under these two themes is to examine their extracted factors from two perspectives: ‘does this factor play a role in the formation of cascading failures and shock propagation?’ or ‘is this factor crucial in increasing the system’s readiness to deal with shocks and reduce their effects?’ By stability, as the last IMM concern and the second in terms of the number of publications, we mean a condition in which there is no major disruption of IMM transactions, with no significant deviation of prices from economic fundamentals,

thereby enabling banks to trade liquidity with confidence. A resilient, systemically stable network might experience only minor damage, while in non-resilient, systemically risky networks, even a small shock could cause colossal harm to the entire system (Amini et al. 2016, Detering et al. 2019). Given the above definition, this part of our survey includes studies on a wide range of terms, from market/network resilience to financial stability.

(a) Network Characteristics

The most common factor in the literature, addressed by many researchers in examining stability, is the level of *connectivity* in the IMM network. The conclusions made in most of the research reviewed in this section are very similar to the classic financial system stability observations, the greater the degree of interconnectedness the more stable the system becomes (i.e. fewer bank defaults), as well noted in Acemoglu et al. (2015). However, the greater the interconnectedness of the system, the more susceptible it is to systemic risk (i.e. events which could cause the default of a large number of banks). Thus, interconnectedness creates a ‘robust-yet-fragile’ effect, as highlighted in Allen and Gale (2000). The pioneer attempt by Allen and Gale (2000) was the first study to use network models to examine the stability of a system of interconnected financial institutions. Over time, three distinct points of view on how connectivity, as an essential characteristic of any financial network (including the IMM network), affects stability have emerged among scientists. Although this is not necessarily unique to the IMM, but networks more broadly, this section focuses on research conducted on interbank networks and discusses different and sometimes conflicting perspectives as the main factor influencing IMM stability.

The first group of scholars includes those who believed that more connectivity leads to more stability. Iori et al. (2006) studied IMM networks with homogeneous and heterogeneous banks and found increasing connectivity stabilizes a homogeneous network, but not a heterogeneous one. Li (2011) created an analytical, tiered structured model of contagion risk in banking systems and demonstrated that increasing interbank connectivity has a positive but limited effect on handling the crisis and

reducing contagion effects. Also, the results obtained by Georg (2013) indicated that the positive effect of the linkage on financial stability is monotonous. Besides, the results of exploring the characteristics of contagion in networks with power-law distribution by De Quadros et al. (2015) revealed that more connected networks are more resistant to contagion than others. Moreover, Gaffeo and Gobbi (2015) discovered that stability was increased by interconnectedness considerably when the shocks affected the assets (in borrower side) and conditionally (i.e. dependent on the topological characteristics of the interbank network) when shocks hit the liabilities (in lender side). Furthermore, network simulations by Gonzalez-Avella et al. (2016) suggested that more connected networks with a high concentration of credit are more resilient to contagion than other networks.

Unlike the first point of view, the second believes that connectedness negatively affects stability in combination with other factors. According to Battiston et al. (2012), a further increase in times of financial distress may amplify it through financial acceleration and increase systemic risk in the case of high connectivity. Toivanen (2013) identified the extensive connectivity as a transmission channel for contagion that spreads the financial crisis faster by exposing all the banks to potential losses. Also, Amini et al. (2016) showed that banks involved in network instability have broad connectivity and a large proportion of contagious links. Recently, Q. Gao and Fan (2020) found that reducing interconnection between small banks, along with increasing lending by large banks, improves the stability of the entire system. These findings reinforce the view that in analyzing network stability, more attention should be paid to network topology and the notion of ‘too-connected-to-fail.’

The last group of commenters on the connectivity, which includes the largest number of scholars, describes an ambiguous impact of connectivity in increasing or decreasing IMM stability. They believe that the same factors that contribute to resilience in certain situations may act as significant sources of systemic risk under the influence of other conditions. The pioneering study by Nier et al. (2007) and subsequent studies by Li and He (2011) and then Gaffeo and Molinari (2016) suggested that the effect of the degree of connectivity on network stability is non-monotonic,

meaning that further connectivity, while increasing the spread of contagion, also helps risk-sharing among the network, thereby reducing the capacity of banks to default. They showed that these opposing effects of risk-sharing and risk-spreading interact differently in varying structures. Separate investigations by Ladley (2013), Acemoglu et al. (2015), and Matjaz Steinbacher et al. (2016) revealed that the relationship between connectivity and stability depends on the degree of shock. From this point of view, as long as the adverse shocks affecting banks are sufficiently weak, a more interconnected network is more stable, but as the shocks increase, beyond a certain point, this connectivity serves as a mechanism to propagate shocks, resulting in a more fragile system. Moreover, numerous simulations by Chakraborty et al. (2017) indicated that higher interconnectedness is good for the stability of large banks but not so much for smaller banks. Recently, research by Smaga et al. (2018) using the Polish overnight loan dataset confirmed the above findings and suggested that the impact of connectivity on stability is very ambiguous, depending on the severity of the shock.

In addition to the connectivity, scholars believe that a number of other attributes of the interbank network also affect stability. According to the literature, *closeness centrality* in the IMM network, as a proxy for banks' reputation (M. L. Bech and Atalay 2010, Toivanen 2013), which shows how close they are to each other in the network and highlights the importance of their failure, is an influencing factor. As pioneer research in this field, it was demonstrated by Boss et al. (2004) that the removal of a few hubs in the Austrian banking network had a significant impact on the stability of the entire banking system. The simulation results of Müller (2006) in assessing the instability of the banking system and the potential for contagion in the Swiss IMM, as well as the computational network model developed by Nier et al. (2007), revealed that the more centralized the market structure is, the greater the likelihood of contagion and the lower the resilience of the network against spillover effects are. Toivanen (2013) argued that when banks are relatively closer to each other, and therefore, the funds' flow across the network is faster, the shock also transmits faster than in a sparse network. Also, the simulations performed by Sachs (2014) confirmed the money center system is more stable than a random graph with homogeneous bank size. On the contrary, according to Imakubo and Soejima (2010b), unlike in Europe and the US,

Japanese IMM participants who act as hubs in the network can, due in part to their relatively high level of liquidity, absorb and limit the contagion.

Another feature of IMM networks that several researchers believe affects stability is *network size*, defined as the number of nodes (M. L. Bech and Atalay 2010). Its positive impact has been addressed by Chakraborty et al. (2017) so that as the number of banks in the network increases, the higher percentage of nodes surviving the shock indicates that the stability of the overall network increases. In another study by Leventides et al. (2019), the likelihood of contagion and, consequently, instability declined as the authors moved the network from smaller to larger settings. These results were recently repeated in an experiment by Sui et al. (2020), who showed that the network's resilience increases with the number of core and periphery banks, respectively.

From the perspective of weighted networks, researchers also do not agree on the correlation between the *number and size of interbank exposures* and stability. Nier et al. (2007) believed that increasing the size of interbank liabilities leads to increased default risk and decreased stability. The results obtained by Detering et al. (2019) regarding the weights of vertices in the network as the influencing factors of resilience can be considered in the same direction. On the opposite side, Jiang and Fan (2019) considered that interbank loans could compensate for the lack of temporary liquidity, as the most important material in the interbank network, and that they play an essential role in the network's stability. They argued that if interbank lending decreases, banks with insufficient liquidity can only sell assets to make up for liquidity, which reduces their profitability (even negative difference between investment and deposit rates), which further results in liquidity tensions in banks and system instability. As a two-sided argument, Ladley (2013) concluded that by constraining the size of interbank loans, the number of bankruptcies due to large shocks would be reduced, but the opposite is true for small shocks. By the same token, using a simple agent-based model developed for analyzing the impact of interbank lending on the financial sector's stability, Lengnick et al. (2013) found that although the interbank exposures stabilized the economy in the expected time, it amplified systemic instability, contagion, and

cascading failures in the network during the crisis. Also, according to T. Xu et al. (2016b), middle-level interbank exposures could effectively protect the banking system from financial contagion, but too small or too high values might be detrimental to network stability.

Concerning the provision of market liquidity by particularly the central bank – as a supplement to the interbank exposures by a regulatory node in the network – many researchers, such as Freixas et al. (2000) and Georg (2013), believe that it could prevent bank failures and systemic risk in this way and thus improve financial stability. Therefore, this action should be considered just as a temporary stabilizing strategy that is ineffective in the long run (de Walque et al. 2010, Toivanen 2013, Mancini et al. 2016). In this regard, the results of a study of the Russian banking sector by Kares et al. (2008) suggested that the central bank’s intervention could effectively reduce coordination failures in the IMM. However, Kikuchi et al. (2016), using an agent-based simulation platform, illustrated that although central bank financing may prevent market collapse by easing cash-flow situations, other risks such as financial institutions’ dependency on the central bank budget and moral hazard are likely.

Besides, according to Li and He (2011), scale-free networks have the highest resistance to shocks and small-world networks vice versa. Due to this fact that small-world networks are characterized by local clustering and shortcut ties that reduce the path-length between the clusters, while scale-free networks take a skewed *degree distribution* (Aarstad et al. 2013), we infer that this difference in market stability is related to the asymmetry of distribution in the network, as seen in technological diffusion on social networks (Jackson and Rogers 2007). However, the model of an interbank market with heterogeneous financial institutions developed by Lenzu and Tedeschi (2012) suggested that the belief of less sensitivity of the scale-free network to domino effects due to the presence of many isolated clusters is incorrect. They argued that the scale-free network develops heterogeneous distributions and therefore creates higher exposures to the network that means instability. Concerning this topic, the result obtained by Gonzalez-Avella et al. (2016) supported this idea that asymmetry in the distribution is a positive factor as long as the network is more concentrated in the

distribution of credits. The skewness in the degree distribution is due to the extensive or intensive margin of credit during normal and crisis times (Blasques et al. 2018). The strategy that banks diversify their lending relationships (i.e. extensive margin) or condition them (i.e. intensive margin) affects the stability of the network (Gabrieli and Georg 2014, Bräuning and Fecht 2017).

In another thread of studies, Toivanen (2013) considered the network's *clustering coefficient*, i.e. the probability that a bank's counterparts are also counterparts to each other (M. L. Bech and Atalay 2010), to highlight the importance of local clusters in the IMM. The authors showed that if these clusters consist of banks with high interbank loan volumes, one of these banks' failure could be detrimental to financial stability. Also, Tabak et al. (2014) evaluated clustering coefficients for the Brazilian IMM network and found that these measures were widely varied in banks and negatively correlated with market stability through interest rate changes.

(b) Capital Requirement

The minimum *capital requirement* for banks is another recurring factor in stabilizing the network by reducing the systemic impact of those banks that are potential hubs for default spread. Müller (2006)'s finding on improving the IMM network's resilience to spillover effects using higher capital buffers and confirming the non-linearity of this relationship by Nier et al. (2007) occurred before the financial crisis of 2007–2008. After that incident, simulations by de Walque et al. (2010) using US market data, the computational model developed by Amini et al. (2016), the results obtained by Matjaz Steinbacher et al. (2016), and the simulation of both homogeneous and heterogeneous IMM networks by Chakraborty et al. (2017) all showed that although the resilience of a network to shocks is a feature that depends on its detailed structure, in all interbank network structures, imposing a minimum capital ratio increases the resilience to shocks. Also, analyzing financial leverage data from the US banking system by Kuzubas et al. (2016) revealed that an idiosyncratic shock would be better handled if banks with higher leverage were asked to hold higher capital.

Another related work is the study by Gaffeo and Molinari (2016), who found that having adequate capital by financial institutions is a prerequisite for their merger to reduce systemic risk by creating a highly interconnected large bank that acts as a hub. Besides, T. Xu et al. (2016b) repeated Nier et al. (2007)'s conclusion regarding the non-linear relationship of stability and capital requirement in a dynamic IMM network model. Moreover, Erol and Ordonez (2017) warned that although capital requirements and other forms of leverage constraints naturally increase network stability, they may cause a sudden collapse in interbank relationships. Recently, Detering et al. (2019), by developing a random graph model for financial networks and using Brazilian IMM data, demonstrated that only large banks' capital in the network matter for resilience. However, Q. Gao and Fan (2020) did not believe in the regulatory policy of setting a unified capital conducive to the banking system's stability and instead proposed adjusting the required capital of banks based on their contribution to systemic risk.

In other related studies, the notion of equity requirement (i.e. a certain threshold for the ratio of equity at market prices over risk-weighted assets) was considered in the study of the impact of regulatory changes on stability by Ladley (2013) and the IMM network model developed by Aldasoro et al. (2017). These studies suggested that higher equity (as a component of tier 1 capital) ratio decreases shock transmissibility within the market at no cost by reducing the number of banks that cause other banks to fail. Furthermore, Souza (2016), as well as Hübsch and Walther (2017), focused on the capital buffer in their studies, concluding that the higher the capital buffer of banks, the less the likelihood of compliance loss and the need to put assets to fire-sale due to stronger shocks, which means that significant stability would be achieved.

(c) Liquidity Requirement

An appropriate *liquidity requirement* is another critical factor affecting stability; because, as mentioned earlier, liquidity deficit can lead to market instability. In this case too, researchers' studies have yielded different results. The study by Müller (2006) on the adequacy of the liquidity buffer suggested that the higher amount of liquidity in the IMM leads to greater market resilience. Also, according to Amini et al. (2016), by

setting minimum reserve requirements for those nodes that have a large number of contracts with other nodes, financial stability would be significantly increased. In another work, Davis et al. (2019), who examined the capacity of liquidity regulations to improve the stability in terms of reducing the number of bankruptcies by both single idiosyncratic and compound shocks, found that in the simple shock regime, liquidity regulations could reduce the incidence of bankruptcy. In this regard, findings by Ferrara et al. (2019) emphasized the importance of post-crisis liquidity requirements in ensuring market stability.

Contradictorily, Iori et al. (2006) found that when banks are homogeneous, higher reserve requirements can lead to a higher incidence of bank failures. Also, Li (2011) underlined that although increasing the bank reserve ratio augments single banks' stability to a certain extent, it may lead to instability by causing liquidity problems for banks that have less excess reserves. Later, Ladley (2013) argued that a higher reserve ratio exacerbates contagious events because more banks have to use the IMM to meet their liquidity needs, and Erol and Ordonez (2017) stated that tightening liquidity requirements above a critical threshold can lead to instability and market crash. Recently, Jiang and Fan (2019) showed that the deposit reserve ratio could restrict the use of banks' funds and significantly influence the banking system's stability so that the lower the deposit reserve rate is, the fewer banks have to go bankrupt. They argued that increasing the reserve ratio reduces the margin difference between the investment and the deposit, which will lead to a weaker ability of the bank to deal with risks and increase the probability of default. Also, Popoyan et al. (2020) showed that the liquidity coverage ratio spurs financial instability and increases the pro-cyclicality of banks' liquid reserves. They proposed using a new macro-prudential tool that adds a counter-cyclical liquidity buffer to this ratio to compensate for this.

(d) Liquid Assets Holdings

An essential feature of the financial crisis of 2007–2008 was the loss of liquidity in IMM due to the lack of bank confidence. This suggests that many banks, seeing other banks' failure, were no longer willing to lend in the IMM, which led to a lack of liquidity

and exacerbated the crisis. The amount of *liquid assets* that banks hoard (i.e. do not offer on the market) is another area of interest for researchers as a factor affecting stability, about which there are sometimes conflicting views. Aldasoro et al. (2017) found that liquidity hoarding (i.e. a situation in which the average ratio of a bank's liquid assets to its total assets is more than a specific limit) by lenders reduces the system's resilience to shock. They ratiocinated that it is because, on the one hand, borrowers that are unable to repay their debts transmit direct losses to exposed lenders, and on the other hand, fire-sales of non-liquid assets transmit indirect losses to the balance sheets of other banks. Also, according to Serri et al. (2017), although liquidity hoarding, as a selfish strategy, consolidates a bank's position in the market, spreads financial distress through spin-off effects, such as interest rate hikes and fire-sale spillovers, and because it induces other banks to behave similarly, causes market instability.

By contrast, Brandi et al. (2018)'s simulation of the propagation of liquidity shocks across the network showed that if banks hoard liquidity, the market structure will change, and the new configuration will be more resilient to liquidity shocks because it will be deprived of its ability to provide liquidity to banks. Furthermore, as an intermediate attitude, T. Xu et al. (2016b) explained that IMM network resilience is a non-monotonic function of the percentage of liquid assets, meaning that a moderate increase in liquid assets could increase the resilience, but keeping higher values by banks may lead to the fragility of the network. This alludes that although declining interbank lending seems to reduce the number of bankruptcies under more massive shocks, this reduction will be accompanied by a much larger fall in loan amounts, leading to lower funding and overall economic suffering (Ladley 2013).

(e) Shock Characteristics

As stated by the scholars, different characteristics of *market shocks* (single vs. compound; random vs. targeted; demand-side vs. supply-side; weak vs. strong) can influence stability independently or in combination with other factors. Georg (2013) analyzed the impact of different types of shocks on financial stability and found that standard shocks are by no means subject to contagious effects, but rather are a threat

to systemic stability. Using a computational model, Ladley (2013) showed that a highly connected market in dealing with small shocks shares the risk among members and reduces the likelihood of a contagious failure. However, if systemic shocks are large, interbank connectivity propagates failure effects and reduces stability. Similarly, in the model developed by Souza (2016), the amplification of losses (i.e. instability) in the Brazilian banking system increased with the shock magnitude. This was consistent with the findings of Matjaz Steinbacher et al. (2016), who used a network-based structural model of credit risk to demonstrate that the likelihood of contagion and loss of network stability increases with the magnitude of systemic shocks because large shocks weaken capital within the banking system, making banks more vulnerable to the counterparty and market risk in subsequent periods. Also, according to Chakraborty et al. (2017), higher severity of shocks leads to many severe damages to the IMM network (i.e. decreases the stability). As can be seen, all researchers agree on the harmful effects of shocks on market stability.

(f) Imbalanced Interbank Position

According to the literature, an *imbalanced net interbank position* is another factor that accelerates contagion effects and, therefore, significantly destabilizes the IMM network. Toivanen (2013) analyzed the importance of individual bank-specific factors on financial stability in Europe and suggested that the bankruptcy of a bank with a large volume of interbank loans and numerous counterparts positioned in a cluster of banks with similar characteristics is detrimental to financial stability. Moreover, in order to analyze the impact of the structure of the matrix of interbank liabilities on financial stability, Sachs (2014) generated a variety of exposure matrices by adding the unequal distribution of interbank liabilities to Nier et al. (2007)'s model and observed a decrease in the network resilience due to this heterogeneity. Hübsch and Walther (2017) also developed a model of realistic inhomogeneous IMM networks found in the real-world and demonstrated an unequal distribution of net interbank exposures (for banks with high net interbank lending or borrowing position) significantly increases instability. All these findings indicate that heterogeneity in the net position of banks in the market positively affects stability.

(g) Banks' Size

Another factor whose impact on financial stability has been studied by several scientists is the *banks' size* in the network. Lengnick et al. (2013) argued that because the existence of large banks threatens the stability of the interbank network, the regulatory policy should target large banks more strictly than small ones. By contrast, Matjaz Steinbacher et al. (2016) argued that large banks are much more resilient to shocks than smaller ones, and if capitalized enough, they can act as stabilizing entities and stop the spread. Recently, Sui et al. (2020) repeated this experiment separately for core and periphery banks in the network. Their study on financial contagion in core-periphery interbank networks suggested that increasing the size of core banks increases their resilience to initial liquidity shocks and periphery banks' failure. They argued that a core bank's large enough failure also leads to the contagious failure of all periphery banks in the same sector. This could be one of the reasons why smaller banks are welcome, especially in times of economic distress (Dermine 2000, Uhde and Heimeshoff 2009, Gaffeo and Molinari 2016), to merge and form a larger bank that can act as a liquidity hub in the IMM network. Recently, Leventides et al. (2019) focused on the size heterogeneity of banks in the network and, using Monte Carlo simulations and a simple default model of contagion, investigated the fragility of several network topologies and observed in their numerical simulations that an interbank network consisting of banks of different sizes could withstand a shock more efficiently.

(h) Less Common Factors

At the end of this section, we refer to the less-studied factors in the publications identified during the review process. In three separate studies, Zlatić et al. (2015), Poledna and Thurner (2016), and Leduc and Thurner (2017) proposed a regulatory mechanism for *systemic risk taxation*. They claimed that by trying to avoid paying tax on each systemic risk-increasing transaction, banks would restructure the IMM network over time so that cascading failures could no longer occur. This process leads to a sustainable, self-organized, self-stabilizing mitigation of systemic risk, enabling the

regulator to effectively restructure the IMM to make it more resilient to insolvency cascades, without sacrificing transaction volume.

In another thread of studies, the interest rate was the scholars' main focus. Through a series of agent-based simulations, Barroso et al. (2016) confirmed that the narrower *interest margins* of banks lead to lower contagion and are associated with further development of the system and thus more excellent stability, which earlier was mentioned in macroeconomic research (e.g. see Brock and Suarez (2000) and Dietrich et al. (2015)). The authors also emphasized using a clearinghouse in an unstable scenario, characterized by high interest spreads, successfully mitigated contagion risk and strengthened the stability. Moreover, first Blasques et al. (2018) and then Popoyan et al. (2020) suggested that *widening the interest rate corridor* has a destabilizing effect on the market as more loans are settled outside of established relationships. They also acknowledged that the existence of an *asymmetric corridor* has a positive effect on controlling interbank rate volatilities and achieving stability.

The last two identified factors are related to secured loans, especially the repo market. Mancini et al. (2016) found that *anonymity* in central counterparty-based trading is an essential factor for repo market resilience because the central counterparty bears the risk of banks, and the borrower and lender remain anonymous and have no direct exposure to each other. Their study on repo markets suggested that holding eligible *collateral* securities by banks could always stably satisfy their liquidity needs in the interbank repo market, even during severe crisis periods. Table 2.10 summarizes all of the topics covered in this section.

Table 2.10. The factors affecting 'stability'. The table lists the influencing factors on the banking system's stability and the actors' strategies for these influences.

Affecting factor	Impact	IMM actors' strategies	Supporting literature
Network: connectivity	Negative	BB: Partially liquidate projects to keep themselves stable LB: Reduce lending to small banks, if small themselves	(Nier et al. 2007, Li and He 2011, Battiston et al. 2012, Ladley 2013, Acemoglu et al. 2015, Amini et al. 2016, Gaffeo and Molinari 2016, Matjaz

			Steinbacher et al. 2016, Chakraborty et al. 2017, Smaga et al. 2018, Q. Gao and Fan 2020)
	Positive	BB and LB: Diversify exposure across different systemic events LB: Lend multiple small banks; increase lending to banks of any size, if large themselves	(Iori et al. 2006, Nier et al. 2007, Li 2011, Li and He 2011, Georg 2013, Ladley 2013, Acemoglu et al. 2015, De Quadros et al. 2015, Gaffeo and Gobbi 2015, Gaffeo and Molinari 2016, Gonzalez-Avella et al. 2016, Matjaz Steinbacher et al. 2016, Chakraborty et al. 2017, Smaga et al. 2018)
Network: centrality	Negative	CB: Provides emergency liquidity assistance to ailing banks in the network	(Boss et al. 2004, Müller 2006, Nier et al. 2007, Toivanen 2013, Sachs 2014)
	Positive	LB: Provide intraday surplus funds	(Imakubo and Soejima 2010b)
Network: size	Positive	BB and LB: Are connected to many large or small banks, if large themselves, else, are connected only to a few small banks	(Chakraborty et al. 2017, Leventides et al. 2019, Sui et al. 2020)
Network: number & size of exposures	Positive	BB: Borrow liquidity deficit LB: Lend excess liquidity CB: Guarantees credit line; bailout	(Freixas et al. 2000, Kares et al. 2008, Georg 2013, Ladley 2013, Lengnick et al. 2013, Kikuchi et al. 2016, T. Xu et al. 2016b, Jiang and Fan 2019)
	Negative	LB: Restrict exposures in the midst of the financial crisis	(Nier et al. 2007, Ladley 2013, Lengnick et al. 2013, T. Xu et al. 2016b, Detering et al. 2019)
Network: degree distribut.	Positive	LB: Reduce the amount of loans that they grant in response to an increase in perceived counterparty risk	(Li and He 2011, Gonzalez-Avella et al. 2016)
	Negative	BB: Enter into agreements with many lenders	(Lenzu and Tedeschi 2012)
Network: clustering coefficient	Negative	BB: Change exposure due to changes in interest rates	(Toivanen 2013, Tabak et al. 2014)
Capital (equity) requirement	Positive	BB: Hold an optimal percentage of capital relative to risky assets; sell non-liquid assets; rebalance portfolio; perform a fire-sale to meet the requirement	(Müller 2006, Nier et al. 2007, de Walque et al. 2010, Ladley 2013, Amini et al. 2016, Gaffeo and Molinari 2016, Kuzubas et al. 2016, Souza 2016, Matjaz Steinbacher et al. 2016, T. Xu et

2.4 | RESULTS OF INTEGRATIVE REVIEW: THE AFFECTING FACTORS

		CB: Sets minimum values; proposes a merger of low-capital banks	al. 2016b, Aldasoro et al. 2017, Chakraborty et al. 2017, Erol and Ordonez 2017, Hübsch and Walther 2017, Detering et al. 2019)
Liquidity reserve/ requirement	Positive	CB: Sets the minimum liquidity requirement	(Müller 2006, Amini et al. 2016, Davis et al. 2019, Ferrara et al. 2019)
	Negative	LB: Preemptively hold liquid assets before stress occurs CB: Sets the minimum liquidity requirement; holds cash reserve	(Iori et al. 2006, Li 2011, Ladley 2013, Erol and Ordonez 2017, Jiang and Fan 2019, Popoyan et al. 2020)
Liquid assets holdings	Negative	BB: Replace shocks with external liabilities LB: Invest in non-liquid assets; raise interest rates	(T. Xu et al. 2016b, Aldasoro et al. 2017, Serri et al. 2017)
	Positive	BB: Deal with stress once it arrives by buying liquid assets or forming new relationships; access to funding from external channels LB: Hoard safe assets/cash CB: Injects liquidity in the market	(T. Xu et al. 2016b, Brandi et al. 2018)
Shock characteristics	Negative	CB: Injects liquidity to the market when shocks are large	(Georg 2013, Ladley 2013, Souza 2016, Matjaz Steinbacher et al. 2016, Chakraborty et al. 2017)
Imbalanced position	Negative	CB: Sets the regulatory capital according to the banks' market position	(Toivanen 2013, Sachs 2014, Hübsch and Walther 2017)
Bank size	Positive	BB and LB: Initially absorb shocks if they are very small or very large	(Matjaz Steinbacher et al. 2016, Leventides et al. 2019, Sui et al. 2020)
	Negative	CB: Imposes more restrictions on large banks	(Lengnick et al. 2013)
Systemic risk tax	Positive	BB: Look for credit opportunities that do not increase systemic risk LB: Propose rates lower than the reservation rate CB: Designs a transaction-specific tax	(Zlatic et al. 2015, Poledna and Thurner 2016, Leduc and Thurner 2017)
Interest: margin	Negative	CB: Regulates the margin by the clearinghouse	(Barroso et al. 2016)

Interest: corridor width	Negative	CB: Determines the optimal values	(Popoyan et al. 2020)
Interest: corridor asymmetry	Positive	CB: Manages the symmetry of the interest rate corridor	(Popoyan et al. 2020)
Anonymity	Positive	CB: Prevents direct exposures of borrowers and lenders to each other	(Mancini et al. 2016)
Collateral	Positive	BB: Borrow on collateral LB: Lend on collateral	(Mancini et al. 2016)

BB–borrower banks; LB–lender banks; CB–central bank

2.5 FUTURE RESEARCH DIRECTIONS

In order to identify trends and directions for future research on IMM concerns before thematically categorizing the extension points suggested by the authors, we have studied a collection of these suggestions through text mining to discover both commonly used themes in this regard and thematic evolution. Accordingly, we searched for the trend topics based on the repetition of words more than five times a year in the ‘future research’ parts of the reviewed publications. For the years before 2013, we could not find any terms repeated more than five times, but for the next years, among the many words reported, we have identified nine specific terms related to IMM concerns as trend topics. Other terms that are either very general or are applied to describe the topics we have identified have been left out of this list. Based on the themes identified in this stage, we outline directions for research on IMM concerns as follows:

1. *Stability*— One of the main concerns we identified for the interbank market in this study is stability. Despite the large number of documents produced in this field, scholars still believe that more research could be added to enrich the literature in this field. Some of the most important questions raised by them in recent years are: What are the effects of heterogeneous balance sheet structures on the banking system’s stability

(Birch and Aste 2014)? How long would the system need to recover from an abrupt loss of confidence as it happened in 2008 (Lux 2015)? Is there an endogenous mechanism in which a given network would work towards a state with maximum stability (Chakraborty et al. 2017)? How to dynamically form interbank networks and the mechanism of temporal financial networks to contribute to the real-time management of financial stability (Kobayashi and Takaguchi 2018)? How can the emergence of too-big-to-fail and too-connected-to-fail banks threaten the stability of financial markets (Popoyan et al. 2020)?

2. *Default*— Researchers believe that finding more accurate ways to predict the likelihood of default of banks, as one of the starting points for the spread and occurrence of systemic failures, so that it can include exogenous spillovers (Brandi et al. 2018) plays an essential role in predicting and managing systemic risk. Among the various factors that affect this probability, we can mention the geographical area (regional or international) of the bank's activity (Birch and Aste 2014), regulatory policies (Lengnick et al. 2013), the state of the economy and/or crisis (van Lelyveld and Liedorp 2006), interbank contagion risk (Li et al. 2015), the dynamics of recovery rate on interbank assets and external assets (Battiston et al. 2016), and temporal aspects of the interbank network (Karimi and Raddant 2016).
3. *Network structure*— Studying the evolution of the interbank network structure and determining how even small and temporary changes in market parameters can lead to sometimes enormous and long-term consequences in the market structure is another topic of interest for researchers for future research. Considering a more vital role for uncertainty in more extensive networks combined with the likelihood of further changes due to more realistic asymmetric structures (Duffy et al. 2019) and evaluating the influence of a group of factors; including policy measures (Gai et al. 2011), different types of credit (e.g. longer maturities

and presence of collateral) (Barucca and Lillo 2018), information asymmetry (Liberati et al. 2015), and banks' behavioral components (e.g. bargaining on interest rates) (Gai et al. 2011, Lux 2015); on these changes are the most important topics suggested by scholars for future research in this field. The study of different types of structure (e.g. hierarchical) and topology (e.g. core-periphery) of real interbank networks is another area that is still of interest to researchers in this field (Ladley 2013, Fricke and Lux 2015).

4. *Balance sheet*— In the absence of accurate information on interbank loan transactions and the need to deduce it from the banks' balance sheets, having more granular balance sheets of banks is vital in research in this field (Calimani et al. 2019). By taking more elements of banks' balance sheets into consideration, a better intuition of the balance sheet will be developed (Li and He 2012), and it is possible to create more diversity in the parameters (Mitja Steinbacher and Steinbacher 2015, Matjaz Steinbacher et al. 2016). Finding innovative methods for building more efficient and accurate models to identify interbank asset classes within banks' balance sheets (Souza 2016) remains a research opportunity in this field.
5. *Central bank*— At present, the vast majority of models developed from the interbank market by researchers lack the central bank as a significant, influential player, making those models far from what is happening in the real world. Hence, many scholars suggest the inclusion of a central bank in their future models as the provider of external safety nets, which acts as the 'lender of last resort' and intervene in the market in the form of bailouts or liquidity injections (e.g. long-term refinancing against collateral) (Iori et al. 2006, Ladley 2013, Lux 2015, Barroso et al. 2016, León et al. 2018, Smaga et al. 2018, Walters et al. 2019). In order to study networks of interbank loans connections that are as realistic as possible, it

is worthwhile for other researchers to introduce the central bank as an active interbank market player in their upcoming research.

6. *Liquidity*— Many researchers have identified the relationship between declining liquidity and several concerns such as the network structure, network stability, and systemic risk in the interbank market (Iori et al. 2006, Taylor and Williams 2009, Lee 2013, Acemoglu et al. 2015) as future goals of their research. A dynamic planning approach to determine the amount of liquidity required by different market members under various circumstances such as uncertainty, loss of confidence, or panic (Iori et al. 2015, Matjaz Steinbacher et al. 2016, León et al. 2018) as well as developing a mechanism that could realize plans and optimally provide liquidity (Berardi and Tedeschi 2017) is one of the essential topics for research in this field. Such a mechanism enables banks to plan and trade in the market not only to meet their immediate needs but also to advance their liquidity needs in the future (Iori et al. 2015). This strand of research covers all types of short-term and long-term liquidity (Lux 2015), secured and unsecured loans (León et al. 2018), with or without central bank intervention (Ladley 2013), and all topologies of the interbank network (Sui et al. 2020).
7. *Contagion*— Future orientation in contagion and systemic risk research, as the main concern of the interbank market, includes three strands. The first would like to theoretically and/or empirically examine the effects of a large number of variables on contagion. The most important of these variables are changes in the volume of liquid assets (Lee 2013, D. Yao et al. 2016), implicit and explicit government guarantees (Ben R Craig and Ma 2018), specific policies of the central bank (Popoyan et al. 2020), targeted shocks (Walters et al. 2019), semi-complete and incomplete network structures (Battiston et al. 2012, Tabak et al. 2014, Erol and Ordonez 2017), different types of interbank loans (e.g. repurchase agreements or non-performing loans), differences in nature and the business of financial institutions

participating in the market, as well as the complex maturity structure of interbank debt (Acemoglu et al. 2015, Leventides et al. 2019). Identifying and introducing new contagion channels and examining the application of existing models in dealing with these channels (Li et al. 2015, T.C. Silva et al. 2016, Hübsch and Walther 2017) is another thread of research in this field. The third strand also studies contagion and systemic risk under the conditions of market environment dynamism, among which we can mention the suggestion of using dynamic game approaches by Erol and Ordonez (2017).

8. *Dynamics*— This is another topic that many researchers are interested in using in their future models, as it allows them to obtain and evaluate results in a more realistic environment. This interest has grown significantly, especially in recent years. One of the uses of dynamics in the field of IMM concerns include its applications in behavioral studies of banks (Mitja Steinbacher and Steinbacher 2015, Halaj 2018, Liu et al. 2018), interest rate dynamics studies (Kusnetsov and Veraart 2019), dynamic formation of interbank networks (Kobayashi and Takaguchi 2018, León et al. 2018), network resistance analysis (Li and He 2011), modeling financial contagion (Erol and Ordonez 2017) and examining the impact of different combinations of macro-prudential and monetary policies (Popoyan et al. 2020). Another strand of future research in this field focuses on methods of implementing network dynamics , e.g. theoretical derivation based on a macroscopic dynamic equation model, which can get a series of conclusions through strict theoretical proof (Jiang and Fan 2019) and using the multi-period approach in developing a fully dynamic model of interbank networks (Kusnetsov and Veraart 2019). An endogenously evolving multi-agent network as a set of contracts among agents that strategically decide what relationships must be formed, maintained or ended (Battiston et al. 2012); optimal intervention by a central bank as a dynamic, stochastic control problem using the approach of the Markov chain (Amini et al. 2016); and financial contagion among interconnected

banks in an incomplete network environment using an explicitly dynamic game approach (Erol and Ordonez 2017) are other examples.

9. *Capital*— As discussed in Section 2.4.2, banks' capital levels are among the most critical factors influencing several market concerns. This factor also plays a vital role in directing future research in this field, especially in recent years. Modeling various types of central bank policies, while the banks could be allowed to recapitalize (Mitja Steinbacher and Steinbacher 2015, Matjaz Steinbacher et al. 2016), considering the total loss of capitalization of the banking system as a robustness indicator (He and Li 2017), empirically analyzing the two possible trade-offs for the role played by higher capital requirements in increasing the resilience of the entire system by strengthening the capital position of individual banks and enhancing contagion by homogenizing banks' balance sheets (Calimani et al. 2019), and investigating the possibility of combining optimal capital allocation approaches for networks and optimal network efficiency approaches for capital allocation (Diem et al. 2020) are among them.

2.6 CONCLUSION

Review articles, whether traditional or meta-analytical or bibliometric, are essential for the development of science; because they make it easier for researchers in those areas better to understand the big picture of their research fields. Besides, these articles provide a baseline in developing the science fields. It means that they reflect what has been done so far and the extent of research progress in that area. This will serve as guidance for future studies and enhance the academic field by providing a summary of what has been done so far and what needs to be done next.

This study aims to identify the most critical concerns of participants of any interbank market, as well as all the factors affecting the concerns. It employs a systematic literature review approach in performing both the bibliometric and

integrative reviews on the IMM field. Using a bibliometric analysis, we were first able to identify the five main concerns of interbank market players: contagion and systemic risk, stability, market structure, relationship and trust, and default and failure. Then, by conducting an integrative review and in-depth study of 160 publications related to the five concerns, we identified and reported the factors influencing (increasing, decreasing, forming, or deforming) each concern. Additionally, we extracted and documented the strategies adopted by each market player in response to the factors from the literature. Finally, the research directions are categorized and presented based on future works considered by the reviewed studies' authors.

Although we have reviewed practical reports and grey literature in addition to peer-reviewed articles from main databases to reduce the likelihood of publication bias; using only five databases, focusing only on the Fed and ECB working papers, and considering only documents produced in English may have somewhat limited the number of included documents and the scope of this survey. Emphasizing that the title or abstract must contain specific terms about IMM and the removal of results containing some irrelevant terms can also be thought of as a limitation. However, the search strategy has identified articles that cover a wide range of money market issues and are not limited to IMM.

Evaluating and managing the quality of the interbank network, as the basis of most research models in this field, is a critical point that we think has been neglected in the literature so far. Similar to quality management frameworks in other areas (Anderson et al. 1994, Evans 2002, Behkamal et al. 2009, Martínez-Costa et al. 2009, Ju and Wei 2011), finding ways to evaluate a set of quality features, such as functionality, security, usability, reliability, availability, predictability, stability, efficiency, supportability, transparency, etc., for the network can ensure its quality for members' activity and facilitate its purposeful management. In such an environment, which can be assessed at any time by measuring quality indicators, the general equilibrium to be solved by researchers in the future will be to maximize the quality of the entire network (macrostructure) as the central bank's goal, and maximize the quality of partial networks among market members (microstructure) as the participating banks' goal.

The latter includes the two issues of node quality (i.e. quality of banks for non-default and non-bankruptcy) and edge quality (i.e. quality of lending relationships).

Another main challenge mentioned by most researchers in this field is the over-confidentiality of market information, especially the information on loan transactions, and the lack of easy access to this information, whether market players' access to their counterparts' information or market analysts', central bank staffs, and scholars' access to the information required for research purposes and stress tests. Accordingly, an opportunity for future research is the study of the mechanisms and effects of securely publishing market data. Although several researchers have already addressed the positive effect of information availability in decreasing systemic risk (Thurner and Poledna 2013, Barroso et al. 2016, Ding et al. 2017) and increasing trust (Affinito 2012, Anand et al. 2012, Marzo and Zagaglia 2014, Ben R. Craig et al. 2015, Renard 2017), conducting comprehensive research on this issue, considering the expectations of all stakeholders, it can even lead to the development of a set of central bank resolutions and instructions to be implemented by all market players. It seems that the advent of Blockchain technology (Nofer et al. 2017, Abadi and Brunnermeier 2018) as the dominant platform for the development of digital fiat currencies in the future (e.g. digital dollar, digital euro, and crypto-yuan) could provide facilities for the secure recording and sharing of the market information (Lewis et al. 2017, Paech 2017).

If classified information is available to all market members, combined with artificial intelligence, it would be possible for banks to predict their counterparts' behavior in bilateral trades and also for the central bank to predict market variables based on the banks' behavior (Alaeddini et al. 2021). Combining these with some research directions gives rise to a possible future study. The idea incorporates a multi-agent architecture (Y. Chen et al. 1999, Raudys and Zliobaite 2006, Liu et al. 2018) to form an interbank network (the third direction) to dynamically manage the liquidity (the sixth direction) required by market members. In this architecture, bank agents are able to price transactions by predicting the probability of default of their counterparts (the second direction) based on the level of their access to market information and what they have learned. The central bank agent can also increase stability (the first

direction), reduce systemic risk (the seventh direction), and boost confidence in the market by applying a set of policies. Indeed, the more realistic strategies adopted by various agents in this environment would greatly help them achieve their goals.

3 SKETCH & DECIDE: AN ARCHITECTURAL DESIGN

AN AGENT-ORIENTED, BLOCKCHAIN-BASED DESIGN OF THE INTERBANK MONEY MARKET TRADING SYSTEM⁷

Abstract. When studying the interbank money market (IMM), it is common to model banks as agents interacting through loans to tackle its complexity. However, the use of agent abstraction in the IMM is mostly limited to some specific cases. Besides, recent advancements show that it is promising to use blockchain technology to improve its security in a decentralized way. Based on this observation, this paper proposes an agent-oriented, blockchain-based design of the IMM trading systems, where the main objective is to decide on the times and methods of liquidity supply and demand by various market players based on what has been learned from the information available. The models in this paper are suitable for use by both academics and practitioners in this field.

⁷ This paper has been presented in the 15th international KES conference on Agent & Multi-agent Systems: Technologies & Applications (AMSTA-21) and published by Springer as a book chapter. Reference as: Alaeddini, M., Dugdale, J., Reaidy, P. J., Madiès, P., & Gürcan, Ö. (2021). An agent-oriented, blockchain-based design of the interbank money market trading system. In *Agents and multi-agent systems: Technologies and applications 2021* (pp. 3-16). Springer, Singapore.

Keywords. Interbank Money Market (IMM), Agent-Oriented Software Engineering (AOSE), Belief-Desire-Intention (BDI), Smart Contract

3.1 INTRODUCTION

The interbank money market (IMM) reallocates liquidity from banks with excess to banks with a deficit via borrowing and lending money at interbank rates. Therefore, the IMM plays a fundamental role in the proper functioning of the banking system and the economy as a whole. The following facts about IMM explain the complexity of decisions in this environment: (i) the secured (collateral-based) and unsecured (trust-based) methods of liquidity provisioning are varied (Acemoglu et al. 2015, Leventides et al. 2019); (ii) the overall demand for short-term liquidity is stochastic (Kobayashi and Takaguchi 2018, León et al. 2018); (iii) there is always the likelihood of domino failures of tightly connected competitors (banks) who lend themselves vast amounts of liquidity (Li et al. 2015, Hübsch and Walther 2017); (iv) it is difficult to access sufficient information from market members (Georg 2014, Fricke and Lux 2015). Moreover, when the central bank intervenes in the market by buying or selling government securities to expand or contract liquidity in the banking system, the decision-making process becomes much more complicated. This complexity affects the decisions of both the central bank as the regulator and banks as active competitors in the market.

Besides, for sending the funds between the banks, the centralized SWIFT⁸ protocol that simply sends the payment orders is used, and also loan agreements between banks ultimately lead to binding contracts for the parties. A promising approach to tackle these issues is to use blockchain technology where an immutable,

⁸ Society for Worldwide Interbank Financial Telecommunication, https://en.wikipedia.org/wiki/Society_for_Worldwide_Interbank_Financial_Telecommunication, last access on 21/02/2021.

append-only, and decentralized ledger of transactions is maintained without a trusted third party (e.g. a central bank). Regarding IMM, blockchain technology has already been started to be adopted. In 2018, the first live securities lending took place with a \$30.5M transaction between Credit Suisse and ING⁹. In 2020, in Italy, thirty-two banks had gone live with one of the first real-world deployments of enterprise blockchain technology in interbank financial markets¹⁰.

To model such complex systems, a well-known approach is to use multi-agent systems (Gürçan 2020). The field of agents and multi-agent systems (MAS) dates back to the late 1980s and the shift in artificial intelligence (AI) to distributed AI (Eduardo and Hern 1988, Hewitt and Inman 1991). However, since the late 1990s, MAS has developed a new method of analyzing, designing, modeling, and implementing complex, large-scale software systems (Jennings et al. 1998, Ferber and Weiss 1999). Agents are software entities that are autonomous within their environment and are able to achieve social ability by exhibiting flexible, reactive, or proactive behavior (Ferber and Weiss 1999). These abilities are facilitated by an agent architecture, known as belief-desire-intention (BDI) (Georgeff et al. 1998), that can model cognitive reasoning.

Standing on these observations, in this study, two issues are addressed to improve the quality of decision-making in IMM. Firstly, since in a static model, the market configuration cannot quickly adapt to (un)intentional changes because the market design is predetermined (Liu et al. 2018, Liu et al. 2020), we propose a MAS model where the market can be dynamically rebuilt at runtime, resulting in a more nimble, flexible and stable system. Secondly, since recording loan transactions in a distributed ledger can lead to greater transparency, security, traceability, and efficiency and reduce

⁹ How Blockchain Could Disrupt Banking, <https://www.cbinsights.com/research/blockchain-disrupting-banking/>, last access on 21/02/2021.

¹⁰ Interbank Market Sees Live Deployment of Blockchain Technology in Reconciliation Process, <https://financialit.net/news/blockchain/interbank-market-sees-live-deployment-blockchain-technology-reconciliation-process>, last access on 21/02/2021.

costs arising from information asymmetry (Pesch and Sillaber 2018, Yu et al. 2018), we propose blockchain technology and its features for better designing the proposed system.

Concretely, the contributions of this paper are threefold: (i) an agent-based software architecture that supports all the functions and concerns associated with liquidity supply and demand; (ii) use of learning agents in system design; and (iii) use of blockchain as part of the architecture of the target system. To this aim, Section 3.2 gives background information about the IMM as a complex system and MAS applications in IMM. In Section 3.3, an agent-oriented, blockchain-based model of an IMM trading system is proposed. It also gives more details about the proposed architecture by providing an example covering both blockchain and learning. The main success scenarios based on this model are given in Section 3.4. Finally, Section 3.5 concludes the paper and gives future works.

3.2 BACKGROUND

3.2.1 IMM as a Complex, Large-Scale System

In an extensive financial market network, where each node represents several market operations, many entities interact non-linearly with each other, making it a complex system. The centralized IMM is where banks exchange funds with each other using centralized software solutions (central depository system (CDS), centralized trading systems (TS) of third-parties, etc.) to balance their books. In such a market, when the liabilities side of banks' books (e.g. deposits) is lower than the assets side (e.g. loans), they are forced to make up for their lack of liquidity by borrowing from those banks in the market whose liabilities exceeds their assets. This loan might be granted based on prior trust and the preferential relationship between the parties or by using an intermediary platform to connect lenders and borrowers.

Figure 3.1 shows the three most common lending processes in a centralized IMM: preferential (bilateral) short-term lending, central bank’s long-term refinancing, and short- or long-term lending using third-party trading platforms. The first often includes unsecured overnight loans, and the last contains both unsecured short-term loans and secured long-term ones, as well as repurchase agreements (repo). Furthermore, central bank intervention is generally made in the form of long-term refinancing of banks against securities with them and through auctions.

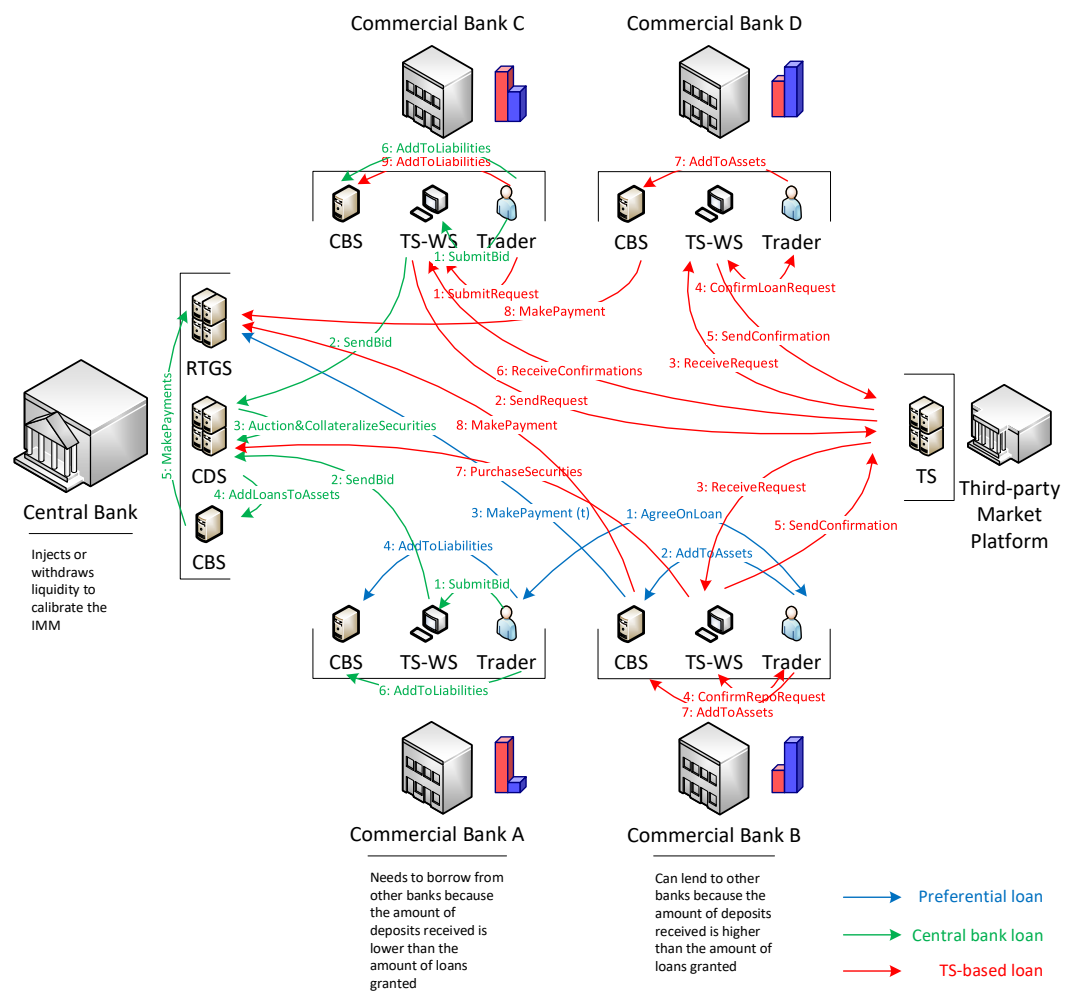


Figure 3.1. The centralized approach of IMM lending. The figure displays the main sequence of preferential loans, central bank’s refinances, and platform-based loans.

In a centralized model, banks record their position loan data and related accounts in their own core banking systems (CBS), all payments are integrated with banks’ CBSs

and made by a central real-time gross settlement (RTGS) system, and securities and auctions are handled in the CDS. Also, banks require special workstations being used by their trading operators to connect to TS and CDS. It is worth noting that banks assess many counterparty risks and make their lending decisions using data provided by rating agencies and financial news providers, which are not shown in Figure 3.1 for simplification.

Another aspect of complexity emerges in supporting the market participants' main concerns and their impact on banks' goals and decisions to supply and demand liquidity. In detail, the central bank seeks to reduce systemic risk and prevent financial contagion (Li et al. 2015, Barroso et al. 2016, Leventides et al. 2019), as well as managing the network (Georg 2014, Acemoglu et al. 2015, León et al. 2018) in a way that makes the IMM more stable and resilient to shocks (Acemoglu et al. 2015, Hübsch and Walther 2017, Leventides et al. 2019) to conserve confidence. At the same time, banks attempt to maintain their lending relationships (Fricke and Lux 2015, Kobayashi and Takaguchi 2018) and reduce the risk of failure to meet the legal obligations (Li et al. 2015, Barroso et al. 2016).

3.2.2 MAS Applications in IMM

An approach to reduce the complexity of a system with such specifications could be to use a self-organizing multi-agent system (Haber 2010). In recent years, much partial research has been conducted using agent-based simulation on various concerns of IMM, i.e. systemic risk (Barroso et al. 2016, Gurgone et al. 2018, Halaj 2018, Calimani et al. 2019, Gurgone and Iori 2019), stability (Gurgone et al. 2018, Popoyan et al. 2020), market structure (Georg 2013, Gurgone et al. 2018), trust (Iori et al. 2015), and default (Barroso et al. 2016, Smaga et al. 2018). To the best of our knowledge, except for a few studies on interbank payment and settlement systems (Galbiati and Soramaki 2007, Rocha-Mier et al. 2007, Hedjazi et al. 2012), a serious complete work may rarely be found on designing an agent-based architecture that can cover all the IMM functions and help to make decisions. Also, the number of studies in which banks have been

modeled as intelligent agents is very limited (Ladley 2013, Georg 2014, Barroso et al. 2016, Liu et al. 2018, Popoyan et al. 2020).

Indeed, a BDI approach, which is able to model each bank's individual concerns, coupled with machine learning, could be useful to improve banks' ability to predict and achieve a competitive equilibrium among market participants. Because the IMM consists of different banks with different and sometimes conflicting goals and proprietary information, a BDI MAS is an excellent option to model their interactions. From a problem perspective, the IMM is a dynamic, complex, and technically open environment in which interaction takes the form of both negotiation and deliberation. From a solution perspective, all three facets of data, resources, and tasks are distributed in the IMM. These features determine that this approach is appropriate for IMM (Bogg et al. 2008).

Also, because loan agreements between banks ultimately lead to binding contracts for the parties, a smart contract that is non-repudiation and transparent (Yang et al. 2019) could lead to a more reliable and trustworthy market. This explains a case where private data needs to be adequately protected in a distributed manner; thus, blockchain could be a potential solution.

3.3 THE PROPOSED MODEL

3.3.1 Agent-based Model

The open architecture components of the proposed system are shown in the UML class diagram in Figure 3.2. The architecture is designed to support emergent behaviors and performance of agents in a volatile environment so that they can provide a higher level of adaptability, discovery, and intelligence. In this approach, each bank has its intelligent agents, i.e. their learning mechanisms that learn their preferences. For instance, in the presence of many banks with different preferences, their agents could

negotiate the optimal interest rates. Also, the central bank agents could enforce the regulations that must be considered by the bank agents as influential factors in the negotiations between them.

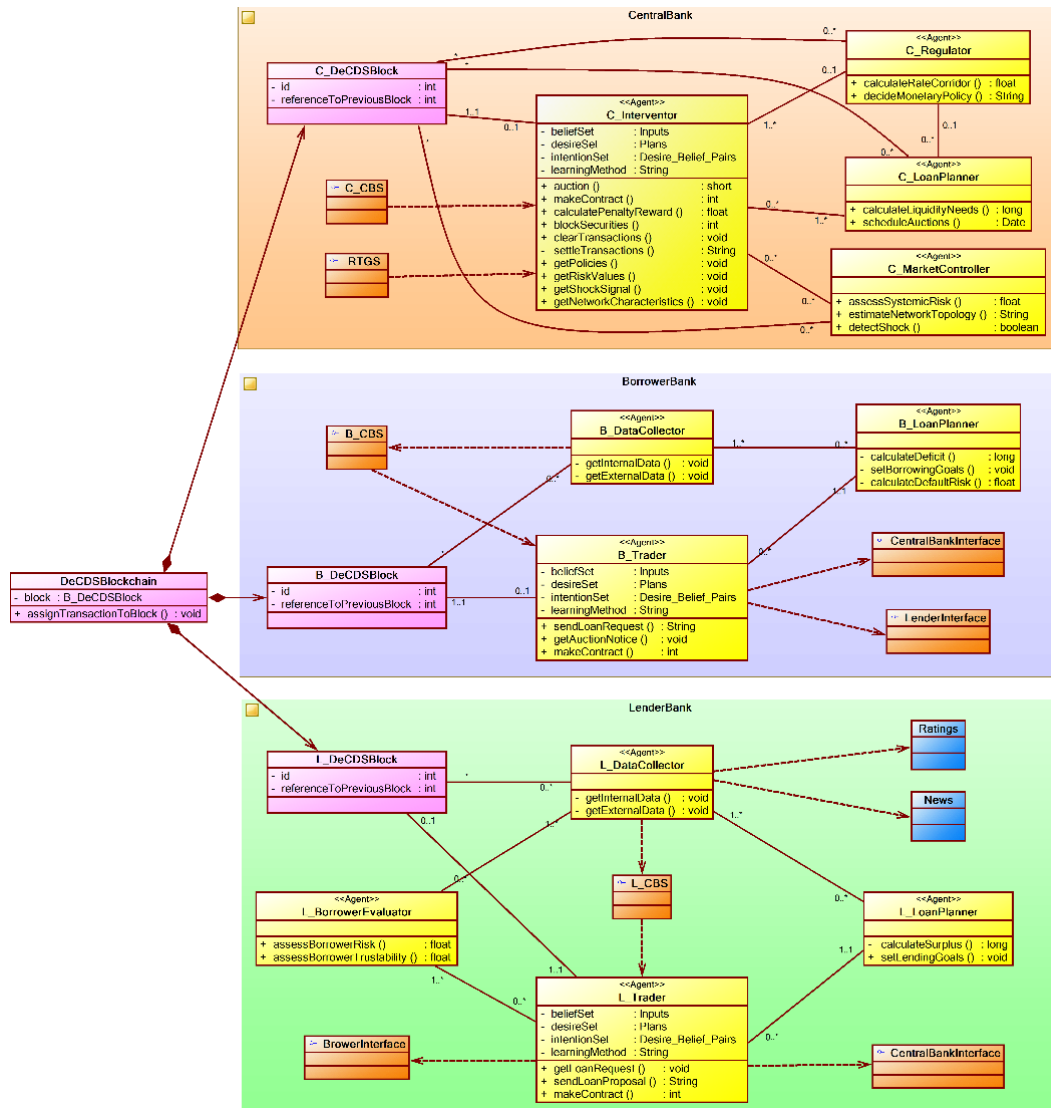


Figure 3.2. The decentralized agent-based approach of IMM. The figure displays the architectural design of holonic agents proposed for the future IMM.

As shown in Figure 3.2, the agents *B_DataCollector* and *L_DataCollector* at borrower and lender banks, respectively, collect information from data sources inside and outside the banks (e.g. news and ratings). Agents *B_LoanPlanner* at borrower banks and *L_LoanPlanner* at lender banks use this information to calculate the deficit or excess of

liquidity and target loans. The central bank's similar agent *C_LoanPlanner* directly uses the data recorded in the bank's blockchain node to plan the total market liquidity needs and refinance it. Banks also use their collected information to assess their own and the counterparty's risks. This is performed at borrower banks via *B_LoanPlanner*'s operation *calculateDefaultRisk*, while at lender banks, agent *L_BorrowerEvaluator* is responsible for that.

The proposed architecture mainly focuses on negotiation behavior among a group of autonomous agents, e.g. how distributed agents negotiate their goals, achieve their goals through planning, etc. Therefore, an intelligent agent at each bank is responsible for negotiating with other banks' agents, meaning several exchanges of requests and proposals, and finally making a loan contract. This function is the responsibility of agents *B_Trader* and *L_Trader* at borrower and lender banks, respectively, and agent *C_Interventor* at the central bank.

As considered in agents *B_Trader* and *L_Trader*, each bank-specific learning method alongside the BDI model would ensure better predictions based on its past preferences and future goals because there is no need to learn all the preferences of all banks. It also means that the bank spends less learning time when faced with a new goal because it uses fewer data over fewer epochs.

The rationale for choosing BDI is that it allows us to model each bank's different beliefs, desires, and intentions, which may even be contradictory. Moreover, it has advantages for the implementation of agents with the characteristics of reasoning, communication, and planning (Norling 2003, Adam and Gaudou 2016). It is also suitable for prediction and performance purposes (Adam and Gaudou 2016). The clear functional decomposition of the agent subsystem and the formal logic properties of BDI are the advantages of this agent architecture over other existing ones, such as traditional logic-based and reactive architectures (Chin et al. 2014). In the proposed model, the BDI agent model's weakness of its inability to support the learning and decision-making characteristics of agents (Rao and Georgeff 1998, Adam and Gaudou 2016) is compensated through machine learning.

In this way, the bank agents present in this smart market take over the negotiation process according to their individual learning mechanisms and by calling each other's interfaces. If some banks have different preferences regarding, for example, interest rates, their agents would first calculate their preferences and then start the negotiation process with other agents, where they must consider the extent of the differences between their preferences. The learning methods that can be applied by each bank are not specified at this level but can include a range of machine learning methods such as supervised, unsupervised, and reinforcement learning (Guerra-Hernández et al. 2004, Guerra-Hernández et al. 2007, Ahmed et al. 2020). Combining these learning methods with the BDI architecture would lead to better decisions by market members (Singh et al. 2011).

As mentioned earlier, a similar learner agent (*C_Interventor*) at the central bank is responsible for market intervention. It uses information produced by other agents (i.e. open market operation objectives set by *C_LoanPlanner*, market variables monitored by *C_MarketController*, and regulations set by *C_Regulator*) to carry out auctions, lending against securities, clearance, and settlement. All data related to loan agreements in the market would be recorded in a distributed general ledger realized by blockchain technology. This means that each bank, as a node in a consortium blockchain network, can participate in the consensus needed to record loan transaction data in blocks. Each bank's agents would also use these data as part of their input, playing a role in making their plans and decisions.

3.3.2 Blockchain and Learning

A blockchain is an append-only immutable data structure of transactions organized as a list of blocks linked using cryptography. It is maintained across several nodes that are linked in a peer-to-peer network (Figure 3.3). A blockchain can manage a self-enforcing agreement embedded in computer code, which is called a smart contract. The smart contract code contains a set of rules under which the smart contract parties agree to interact with each other.

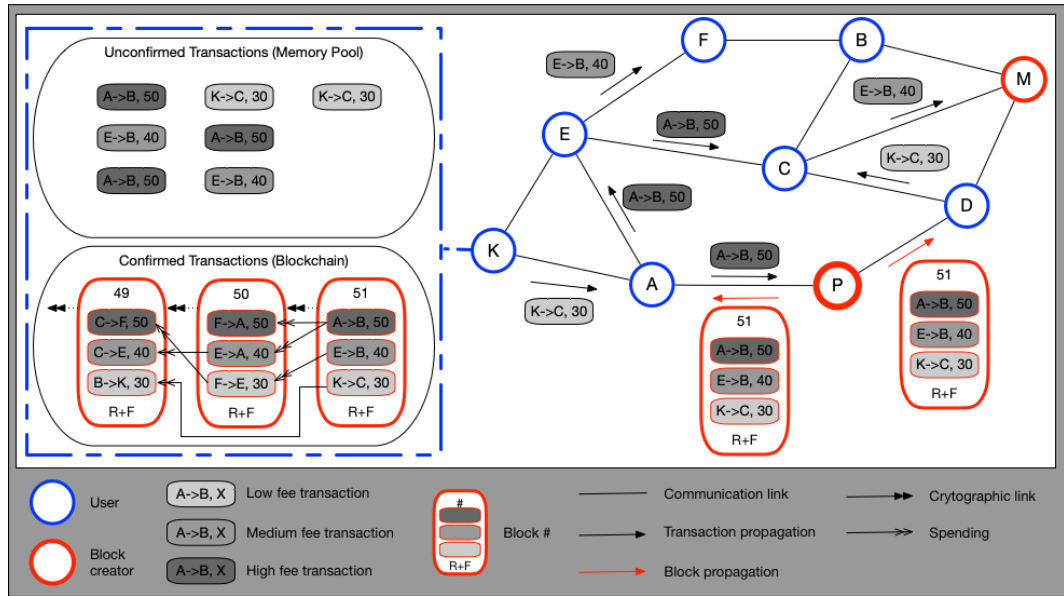


Figure 3.3. Multi-agent representation of a blockchain system. The figure shows a blockchain-based, open, distributed electronic payment system composed of participants called *users* and *block creators*. (Gürçan 2019).

In our study, we consider a blockchain consisting of $N = \{n_1, n_2, \dots, n_m\}$ nodes (banks), of which $P \subseteq A$ are endorsing peers classified into p levels. Each bank uses blockchain for various data categories, e.g. submitting its smart contracts (loan transactions) or sharing common interest information, such as counterparty defaults. The endorsing peers examine these data before being written in the distributed ledger. The block could be written as $B = \{t_{i,j}\}$, where $t_{i,j}$ refers to the transaction j of data category i (corresponding to p levels).

Endorsers calculate each transaction’s score by tracking the number, volume, riskiness, and impact of transactions. When two banks, which agree upon a smart contract and sign it with their private keys, want to add this new transaction to the blockchain, they must collect a minimum prerequisite score from endorsing peers (i.e. consensus). This score is obtained based on recommendations from other related nodes at the moment of submitting the transaction. It means that other nodes check the state of the blockchain, including the exact contract code, and validate that those

parties are whom they say they are. Also, a state transition function checks the behavior and the results of that code when it is executed.

Once a new block is created, all claimed transactions to be included in it are checked for legality by the consensus protocol, and transactions that fail to collect the required score for the selected level are discarded. To reach higher levels, the bank must increase its contributions to the blockchain and make high-impact, trusted transactions. To this aim, the bank uses intelligent mechanisms to make the optimized decision at the right time, based on the available network data as well as its own data. Adapted from Mbarek et al. (2020), the score of a given transaction could be calculated according to Equation 1:

$$S_l = \sum_{i=1}^p \left(\sum_{j=1}^q s_{l,j} \right) w_i \quad (1)$$

where, w_i denotes the weight of the endorsers of level i ; $s_{l,j}$ is the score given to the loan transaction l by the endorsing bank j at the same level that accepts the transaction scoring request. Also, q is the number of required endorsers at that level.

In this mechanism, each member bank in the blockchain network has to establish trust with its peers, especially the endorsing ones. Trust relationships would be particularly helpful in gaining recommendations from higher-level endorsers. In the proposed system, the bank can intelligently identify its current options, plan its actions, and reflect on the results to establish and maintain trust and identify appropriate endorsing partners. As proposed in Figure 3.2, learning is the responsibility of intelligent agents *B_Trader* and *L_Trader* at borrower and lender banks, respectively, and agent *C_Interventor* at the central bank.

Figure 3.4 shows the UML statechart diagram of the loan registration in the system's blockchain, borrowed from its detailed design model. Based on the BDI architecture, 'beliefs' include information that the intelligent agent has about itself (e.g. its current liquidity, market strategies, default risk, etc.) and its surroundings (e.g. network structure, potential/actual banks for a relationship, and events of interest,

such as other banks' defaults and announced auctions). The beliefs also include a copy of the blockchain containing data belonging to the categories to which the agent has access (state *Transacting*). Beliefs can be right or wrong and change over time as the market operates (state *Revising*). In this system, 'desires' reflect the objectives that the agent wishes to achieve and include such things as receiving/granting loans, sharing information, or accepting/refusing other agents' endorsement. Based on the new beliefs, the agent's desires must also be updated (state *Updating*). Finally, 'intentions' refer to the actions that the agent chooses to execute. For each possible action, the agent calculates the reward, cost, priority, etc. Once a set of possible actions is identified, the agent analyzes the calculated results to prepare and execute an action plan (state *Analyzing*). The output of the actions is assessed, and the intentions of the agent are updated accordingly.

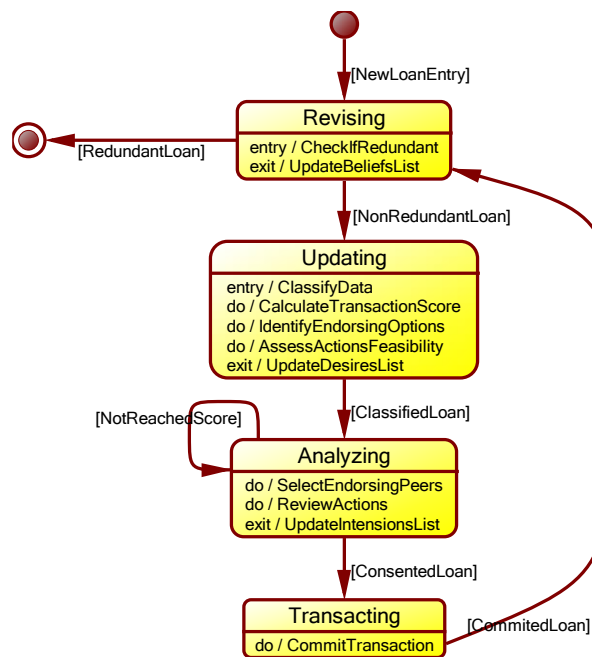


Figure 3.4. States of a loan transaction registered in the blockchain. The figure shows the UML statechart diagram of the loan registration in the system's blockchain based on the BDI architecture.

3.4 MAIN SCENARIOS

In this section, UML sequence diagrams are used to describe how and in what order a group of agents work together in the proposed system to execute the most common IMM scenarios according to Liu et al. (2018), Barroso et al. (2016), and Gurgone et al. (2018). We model two scenarios: one for overnight lending based on trust among banks and another for long-term refinancing by the central bank against banks' securities.

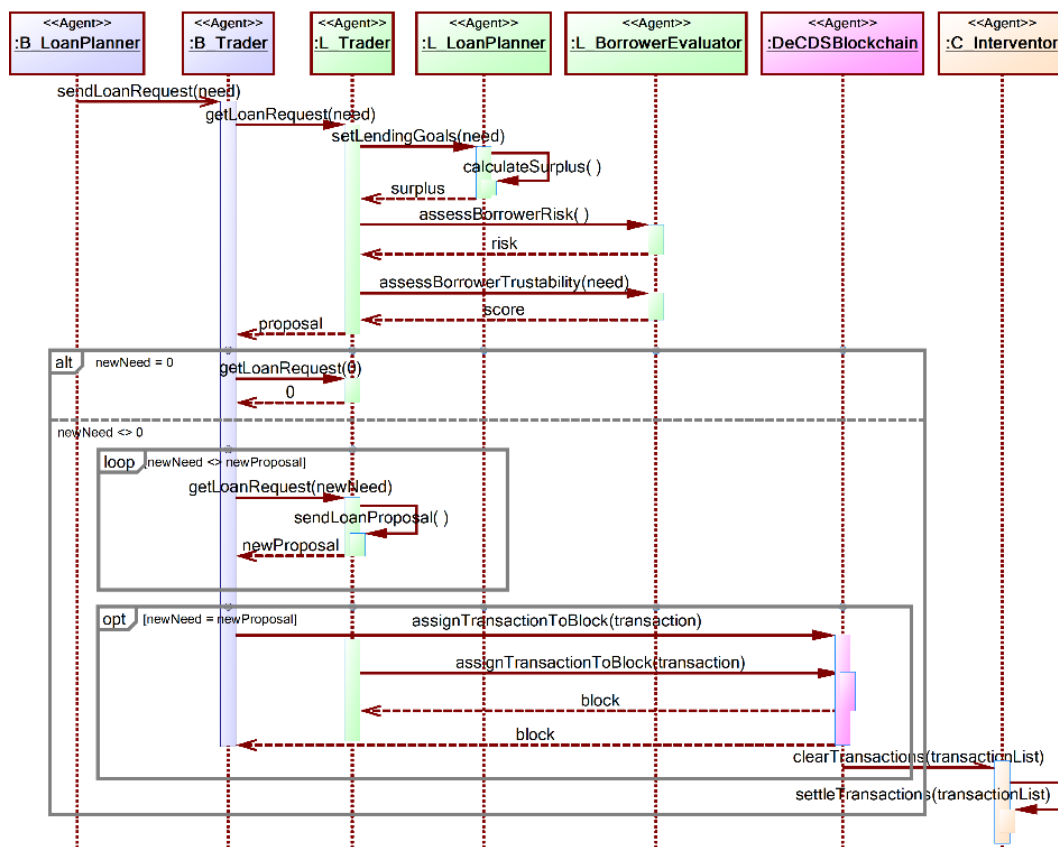


Figure 3.5. Agent-based scenario for overnight loans. The figure shows a UML sequence diagram describing the messages exchanged between agents to perform the overnight lending scenario.

For the first scenario, as shown in Figure 3.5, the borrower bank's agent *B_Trader* uses *need* data generated by agent *B_LoanPlanner* and sends its request to the lender bank's agent *L_Trader*. To decide on the loan terms and conditions, *L_Trader* inquires

the liquidity *surplus* as well as the borrower bank's credit *risk* and trust *score* from agents *L_LoanPlanner* and *L_BorrowerEvaluator*. According to the results of these inquiries, *L_Trader* suggests loan terms (e.g. interest rate) to *B_Trader*. This offer is based on all that *L_Trader* has learned so far about the overnight loan in the smart IMM.

After receiving a *proposal* from *L_Trader*, based on what *B_Trader* has learned, it may immediately accept or reject the offer or enter into a negotiation process with *L_Trader*. As mentioned earlier, the negotiation is based on the learnings of the two agents from their past, market conditions, and other players' behavior and progresses in the form of changing goals and preferences. In any case, if no agreement is reached, the process ends here; otherwise, if the negotiation between the two agents succeeds, a loan transaction based on the loan smart contract would be recorded in a *DeCDSBlockchain block* of each of these two banks as well as other market members.

Finally, the agent *C_Interventor* at the central bank would perform clearance and settlement of the banks' *transactionList* at the end-of-day based on the information recorded based on the smart contracts. Also, the systemic effects of banks in the IMM network could be evaluated by this agent based on these data, and if one bank's transaction is accordingly subject to a reward or penalty by the central bank, the amount is calculated and deducted from that bank's account with the central bank.

The second scenario, in Figure 3.6, starts from the central bank. First, *transactionList* stored in the central bank's *DeCDSBlockchain* blocks is used to determine *policyList* by agent *C_Regulator* as well as calculating systemic *risk*, estimating network *topology*, and detecting possible shock *signal* by agent *C_MarketController*. Similarly, agent *C_LoanPlanner* determines market *need* using *transactionList* and specifies *time* for auctions. *C_Interventor* then receives the results of calculations by these three agents as well as *B_Trader's bid* for the central bank's loan. After auctioning and determining the winners, if a loan is granted to the bank, *C_Interventor* notifies *B_Trader* of *bidResult*.

Like the first scenario, a loan transaction (based on the loan smart contract) would be made between *C_Interventor* and *B_Trader* and stored in a *DeCDSBlockchain block* of

the central bank and the borrower bank, as well as other market participants. The central bank would employ the information stored based on these smart contracts to clear and settle the borrower banks' *transactionList*. Also, the central bank and the other banks use this information in their future forecasts and plans.

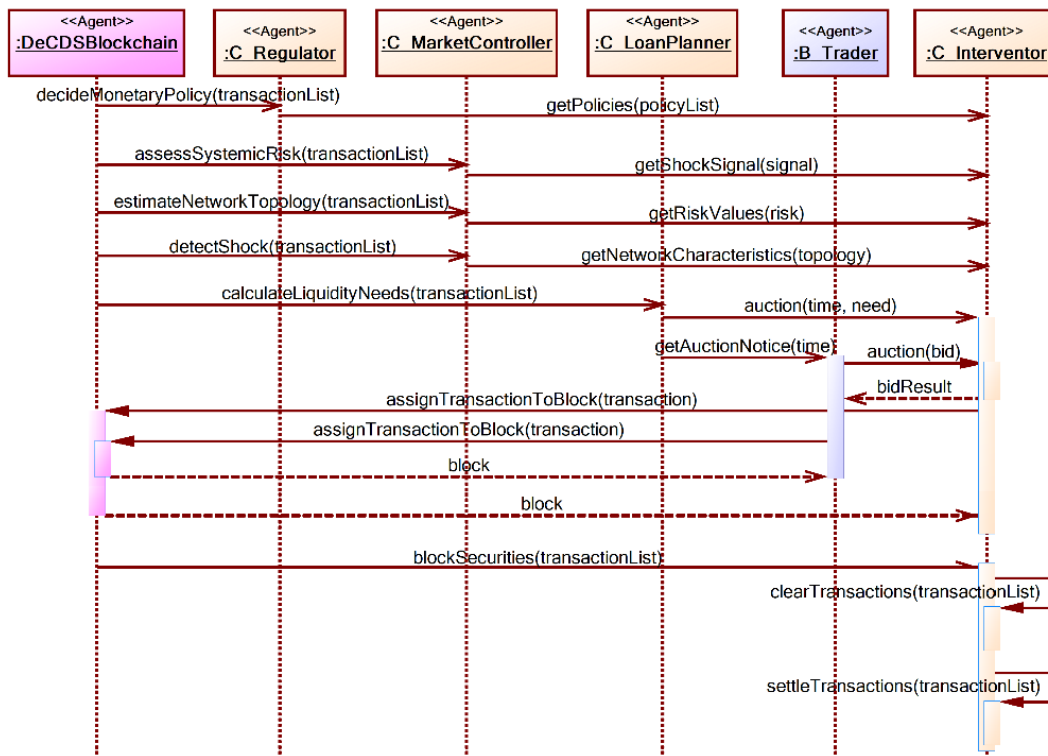


Figure 3.6. Agent-based scenario for central bank refinancing. The figure shows a UML sequence diagram describing the messages exchanged between agents to perform the central bank refinancing scenario.

3.5 CONCLUSION AND FUTURE WORKS

This paper describes a software architecture that uses intelligent agents to execute the interbank market functions and make decisions on behalf of the market actors. In this proposed solution, the BDI architecture is employed to model the cognitive part of the agents and execute goal-based scenarios. Also, data obtained from the interbank lending transactions are recorded and stored in a consortium blockchain platform, of which the banks and the central bank are nodes. To better understand the designed

agents and the mechanisms of using information and learning, some of the most widely used IMM scenarios have been modeled using the UML diagrams.

The main limitation of the work is that only a high-level design is presented, and no part of it has yet been implemented and tested to validate the proposed architecture and ensure performance. Therefore, the next step is the detailed design and implementation of the proposed system prototype. In addition to the full realization and testing of the system, further studies could also be directed at improving the system's machine learning aspect, alongside the greater use of blockchain in designing the new processes required for trading the new financial instruments such as crypto-securities. Agent-based modeling and simulation of the desired system in which agents can learn from each other and their past data when loan transactions are stored in a blockchain network is another topic for future work.

4 PROTOTYPE: A MINIMAL MODEL

EXPLORING CREDIT RELATIONSHIP DYNAMICS IN AN INTERBANK MARKET BENEFITING FROM BLOCKCHAIN-BASED DISTRIBUTED TRUST: INSIGHTS FROM AN AGENT-BASED MODEL¹¹

Abstract. Trust is crucial in economic complex adaptive systems, where agents frequently change the other side of their interactions, which often leads to changes in the system's structure. In such a system, agents who seek as much as possible to build lasting trust relationships for long-term confident interactions with their counterparts decide whom to interact with based on their level of trust in exist-ing partners. A trust crisis refers to the time when the level of trust between agents drops so much that there is no incentive to interact, a situation that ul-ti-mately leads to the collapse of the system. This paper presents an agent-based model of the interbank market and evaluates the effects of using a voting-based consensus mechanism embedded in a blockchain-based loan system on main-taining trust between agents and system stability. In this paper, we rely on the fact that blockchain as a distributed system only manages the existing trust and does not create it on its own. Furthermore, this study

¹¹ This paper has been presented in the 17th annual Social Simulation Conference (SSC2022). Reference as: Alaeddini, M., Dugdale, J., Reaidy, P. J., & Madiès, P. (2022). Exploring Credit Relationship Dynamics in an Interbank Market Benefiting from Blockchain-based Distributed Trust: Insights from an Agent-based Model. In *17th annual Social Simulation Conference (SSC2022)*, Milan, Italy.

uses actual blockchain technology in its simulation rather than simply presenting an abstraction.

Keywords. Agent-based simulation, Asymmetric information, Confidence, Distributed ledger, Interbank call loan market, Uncertainty

4.1 INTRODUCTION

Trust seems to be a focus in promoting the ability of agents to collaborate across a complex adaptive system (Ramchurn et al. 2004, Kim 2009). Models developed in this area seek to avoid the failure of agents' collaborative efforts by entering them into a relationship in order to collaborate (Wooldridge and Jennings 1999). However, trust may be damaged due to unforeseen changes in the environment. In addition to the agents' selfishness due to different ownerships, which sometimes makes them unreliable, one primary source of mistrust in such systems is their lack of global perspective and complete knowledge of the whole environment and their peers with hidden intentions (Pinyol and Sabater-Mir 2013).

An interbank market, as a highly stochastic economic environment (Mitja Steinbacher and Jagrič 2020), is a complex adaptive system (Glass et al. 2011, Chiriță et al. 2022) where banks lend large amounts of money to each other at interbank rates when they need liquidity in a short period (Alaeddini et al. 2022), thus adapting to this stochastic environment. Establishing more lending relationships in this market helps borrowers with more diverse sources of liquidity (Ben R. Craig et al. 2015) and enables them to borrow at lower interest rates from lenders with whom they have a relationship (Cocco et al. 2009). However, these relationships dynamically change due to the short-term nature of unsecured funding (Anand et al. 2012). In order to preserve credit relationships, maintaining a level of trust is essential for all market participants, as its evaporation can lead to instability and liquidity crises (Alaeddini et al. 2022).

These days, the notion of distributed trust (Abdul-Rahman and Hailes 1998) has been reintroduced through the use of blockchain (Calvaresi et al. 2018a). As a cryptographically secured, distributed ledger, this technology is widely believed to spread trust in digital environments (Shin 2019). In this study, using the aggregate balance sheet of French banks, we model an interbank market as a multi-agent system and examine whether blockchain is able to compensate for the loss of trust among peers during economic declines. Concretely, the contributions of this paper are twofold: (i) adding to the literature on trust in multi-agent systems and (ii) using blockchain as part of the simulation platform. The rest of the paper is organized as follows: Section 4.2 gives background information on related work previously performed in this area. Section 4.3 describes the components of the model and the behavior of various agents in different circumstances. The results of simulating this model based on a number of scenarios are presented in Section 4.4. Finally, Section 4.5 concludes the paper and gives avenues for future research.

4.2 RELATED WORK

4.2.1 Distributed Trust

The notion of distributed trust is not new and dates back to the late 1990s (Abdul-Rahman and Hailes 1998). Among the methods proposed for building trust in multi-agent systems, one can find those that benefit from this notion. Jordi and Sierra (2001) use a reputation mechanism in which each agent records its direct trust in other agents resulting from interacting with them in a local database and shares these data with other agents so that they use them in their indirect trust estimation. Jurca and Faltings (2003) propose a set of broker agents responsible for gathering reports from other agents on their interactions with each other. The broker agents also provide reputation information to agents who need it. Tweedale and Cutler (2006) attribute trust to the collective decision of a hierarchical team of which the agent is a member. Huynh et al. (2006) integrate all of these methods into a framework called FIRE. However, in the

past, there were many obstacles to the objectification and implementation of distributed trust in practice because it is unreasonable to expect such information to be shared by all members of the system (Huynh et al. 2006).

By using blockchain, which refers to a cryptographically secured distributed ledger with a decentralized consensus mechanism, it is easier to implement such ideas. Calvaresi et al. (2018b) provide a JADE-based architecture and implement a system that computes agents' reputations using smart contracts and enables tracking of how their reputation changes. Khalid et al. (2021) propose maintaining trust in an agent-based distributed energy trading system by publishing information on inter-agent agreements in the blockchain. Alaeddini et al. (2021) consider blockchain in designing a multi-agent interbank trading system, where trust is regarded as a significant concern. It is worth noting that none of these studies addresses an individual agent's threshold for the trust it needs to have in another agent to interact, and in fact, they all have given the same recommendation to all agents, regardless of their specific characteristics. Also, none of the models uses a real blockchain as part of their simulation system.

4.2.2 The Selected Trust Mechanism

Unlike the mentioned methods of trust in multi-agent systems, we propose a new method to develop a trust model based on the consensus reached by agents and using some variables found by Bülbül (2013). The following features are the main distinctions of this method from others:

- Both the expected level of trust of the agent responding to the interaction and the level of trust met by the agent requesting the interaction are considered;
- It uses a blockchain-based consensus algorithm to establish distributed trust; and

- Unlike some other methods (e.g. Khalid et al. (2021)), it does not publish any confidential information of agents on the blockchain.

The model uses a reputation system as an additional trust layer based on counterparts' relationships (Pazaitis et al. 2017) and applies six values from -1 (distrust) to 4 (complete trust) for both direct and indirect trust. The value of direct trust is the result of assessing the lender's trust in a borrower for a loan transaction, while an indirect value is based on reputation information. An agent uses values of its direct trust in other agents in order to arrive at a consensus on their reputation and recommend them to other agents.

To calculate the level of trust desired by the lender agents, the model uses three determinants, including current interaction with the central bank ($X_{1_{i,t}}$), equity ($X_{2_{i,t}}$), and size ($X_{3_{i,t}}$) of the lending bank as follows at every time step $t = 1, 2, \dots, T$:

$$X_{1_{i,t}} = \begin{cases} 1, & \text{bank } i \text{ has a debt to the central bank in time } t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$X_{2_{i,t}} = \begin{cases} 2, & \text{bank } i\text{'s capital at time } t > \text{average capital of banks of similar size} \\ 1, & \text{bank } i\text{'s capital at time } t = \text{average capital of banks of similar size} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$X_{3_{i,t}} = \begin{cases} 1, & \text{bank } i \text{ is small in size} \\ 0, & \text{bank } i \text{ is medium in size} \\ -1, & \text{otherwise} \end{cases} \quad (3)$$

$$\tau_{i,t} = \max\left[-1, \left(X_{1_{i,t}} + X_{2_{i,t}} + X_{3_{i,t}}\right)\right] \quad (4)$$

where $\tau_{i,t}$ denotes bank i 's observed ordinal variable as the trust threshold at time t .

Let $\theta_{i,j,t}$ denote the trust level between banks i and j at time t . A lending relationship between lender i and borrower j is allowed at time t if $\theta_{i,j,t} + \tau_{i,t} > 4$. The level of direct trust between banks i and j at time t is obtained from the Equations 5, where $H_{i,j,t}^{good}$ indicates the history of good records of bank j in repaying the loans it

has received from bank i until time t , and $H_{i,j,t,bad}$ denotes the history of bad records in the same period. $H_{i,j,t}$ indicates the number of lending relationships between banks i and j from the beginning to time t .

$$\theta_{i,j,t} \approx \max \left[-1, \left(\frac{H_{i,j,t,good} - H_{i,j,t,bad}}{H_{i,j,t}} \times 4 \right) \right] \quad (5)$$

To calculate the level of indirect trust between two peers who did not have a lending relationship with each other before time t , each agent asks endorsers to examine the level of trust of the new counterpart. Endorsers, which are nodes located in the credit paths leading to the endorsee node, calculate its trust level by tracking the points assigned to that node and their credit paths that lead to it. The final score, subject to consensus, would be obtained based on the recommendations of other related nodes before the time of the loan transaction. The model defines the indirect trust of bank i to bank j as the direct/indirect trust of the counterparts k of bank i to bank j , weighted by the trust of bank i towards these neighbor agents k . Let $w_{i,j,t}$, defined as follows, denotes the elements of the stochastic matrix for normalizing the values of $\theta_{i,j,t}$ ($= 0$ if there is no link between agents i and j).

$$w_{i,j,t} = \frac{1}{4} \times \frac{\theta_{i,j,t}}{n(N_{i,t})} \quad (6)$$

where $N_{i,t}$ is the set of neighbors of agent i at time t , and $n(N_{i,t})$ denotes the number of elements in this set. The indirect trust score of bank i to bank j is calculated as follows:

$$\theta_{i,j,t} \approx \sum_{k \in N_{i,t}} w_{i,k,t} \theta_{k,j,t} \quad (7)$$

This means that in order to calculate the level of trust of a counterpart if there is a direct relationship, agents use Equations 5; otherwise, they need the consensus of other agents based on Equations 7 (maybe in a recursive mode).

4.3 THE MODEL

4.3.1 The Agent-based Simulation System

Our model developed in Repast Symphony builds on a number of recent studies (Sato et al. 2019, Teply and Klinger 2019, Popoyan et al. 2020, Mitja Steinbacher and Jagrič 2020) and is populated by two types of agents: (i) N banks that interact with and lend to each other, and (ii) one central bank that regulates the market and helps banks avoid failure when necessary. Furthermore, a lending contract has been developed to support interactions among the agents.

Banks are heterogeneous, imperfect, autonomous, and, to some degree, adaptive agents. They follow base-level rules to make interbank placements and must meet all regulatory requirements in their transactions and changes in their balance sheets. The initiation stage in our model creates random counterparts for banks, assigns their initial assets and liabilities according to banks' sizes, and determines each bank's balance sheet. The natural and financial sides of the market are linked by multiple, non-linear feedbacks and evolve in a finite time horizon. In each time step (one day), the items on the banks' balance sheets change stochastically by following Gaussian random walks with related moving drifts $\mu_{o_i,t-1}$ and noises σ_{o_i} (see Appendix D for details).

The general logic of the simulation is that banks manage their liquidity (cash) by exchanging funds in the market. It is assumed that, at first, there are no loans to be repaid by banks (none of the banks owes to other banks). After the change in the banks' balance sheets in the first time step, the interaction of banks to borrow funds overnight in order to compensate for their lack of liquidity forms the interbank lending network in our model. Interbank payments settlement is managed by a central clearing counterparty (i.e. the central bank), and all interbank loans are simulated to be paid in the blockchain (see Section 4.3.2). Figure 4.1 shows the sequence of actions performed at each time step.

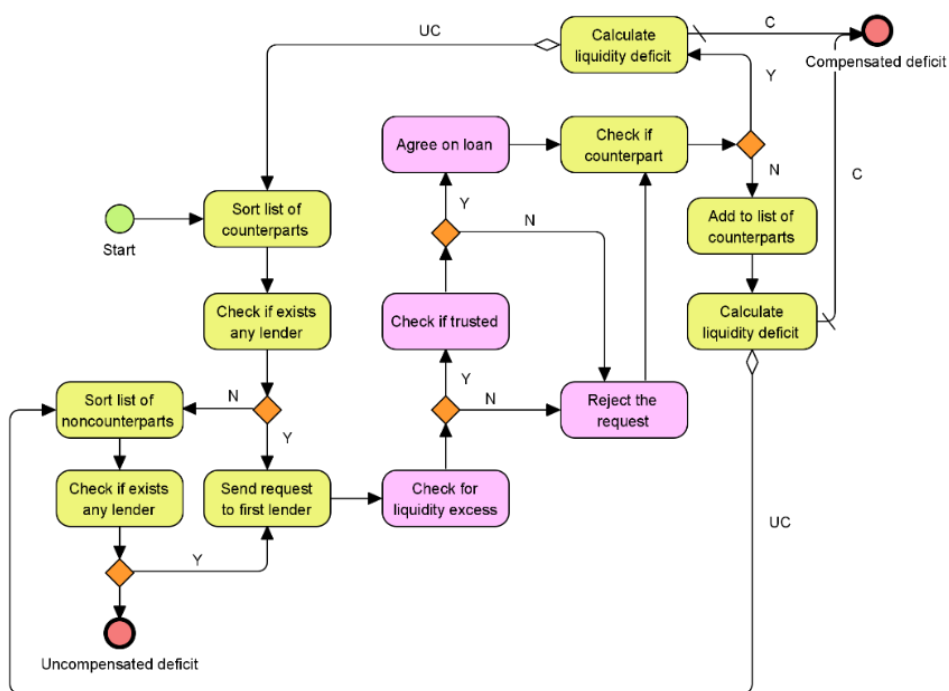


Figure 4.2. The loan process in BPMN (Y: yes; N: no; C: compensated; UC: uncompensated). The figure shows the sequence of actions taken in the demand and supply of liquidity through loans.

As shown in Figure 4.2, in order to manage their liquidity, banks borrow or lend in the market. For this purpose, based on their history, borrowing banks send their loan requests first to their lending counterparts. Lending partners respond to requests based on their excess and borrowing banks' history. If banks cannot borrow from their existing counterparts, they will apply for a loan from other banks with a lending position in the network. If lending banks meet all or part of the liquidity needs of the applicant banks, they adopt two different strategies against the two off-chain (traditional) and on-chain (blockchain-based) modes (see Section 4.4.1). In either case, both borrowing and lending banks add each other to their counterparty list if the loan is agreed upon.

Banks that have not been able to make up for their need in the market will be refinanced by the central bank if they have enough securities; otherwise, they will have to fire sell—selling assets at heavily discounted prices. Then, banks try to repay their overdue loans, if relevant. At the end of each period, a bank goes bankrupt if it fails to

make up for its liquidity deficit or its equity is zero or less and does not compensate for these problems by raising its equity. The failed bank is removed from the model. The bank's failure also leads to losses resulting from its zero debt to the banks from whom it has borrowed. This is the unique source of systemic risk and instability in our model. It is worth noting that the flow diagrams in Figure 4.1 and Figure 4.2 represent real bank behaviors (Sato et al. 2019, Popoyan et al. 2020).

4.3.2 The Blockchain-based Loan System

Adapted from Cucari et al. (2021), we develop a simple loan system on the consortium blockchain Corda that records loan transactions of agents. To develop this system, we use the logic of a simple CorDapp already implemented by the Corda team and make changes based on our specific needs. One of the items that the loan system records and maintains is loan state, which is an immutable object representing facts (i.e. loan data) known only by counterparts. The system also benefits from smart contracts between banks by turning the contract terms into code that executes automatically when they are met. The contract code is replicated on the nodes in the network. All these nodes have to reach a consensus that the terms of the agreement have been met before they execute the contract. Figure 4.3 shows the sequence of consensus in the system.

Loan transactions must achieve both validity and uniqueness consensus to be committed to the ledger. The first determines if a transaction is accepted by the smart contracts it references, while the latter prevents double-spends, i.e. the risk that the money is paid twice or more. A transaction must have all the necessary signatures to reach the validity consensus, meaning that the qualification of a borrower who has no previous relationship with a particular lender must be endorsed by a notary consisting of the banks that have already lent to that borrower. Uniqueness consensus is when the notary checks that the lender has not used the same input for multiple transactions.

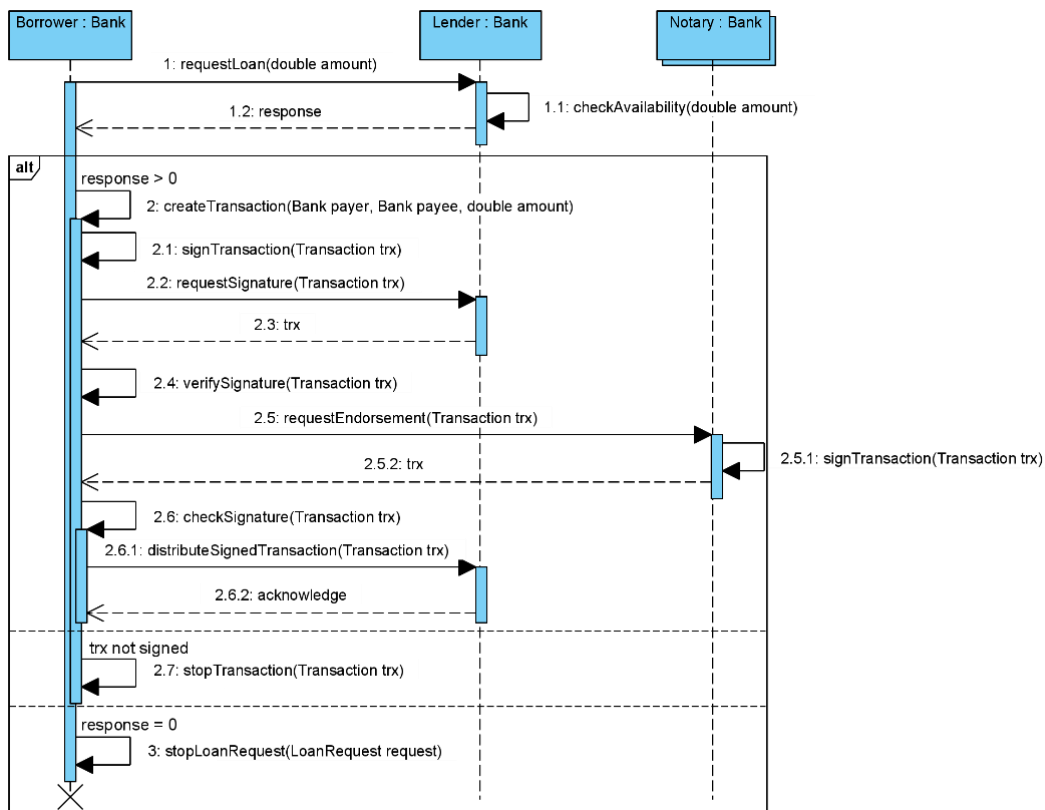


Figure 4.3. The UML sequence diagram of consensus in the blockchain-based loan system. The figure shows the sequence of messages exchanged between different objects in the system to reach a consensus regarding granting a loan.

Communication between banks is point-to-point using a flow, which automates the process of agreeing on ledger updates between the banks. Our agent-based simulator communicates with the loan system through an API that we developed. The initiation stage in our model deploys one node in the blockchain for each agent. The deployed blockchain nodes containing the API that records loan transactions on the blockchain are then run at this stage. Therefore, the environment we implement to simulate agents' behavior is as similar as possible to the real environment that banks may use in a real market by employing a real blockchain to record their loan transactions.

4.4 EXPERIMENTAL EVALUATION

4.4.1 Scenarios

We study the interbank market dynamics with and without using blockchain. We first test three economic cycle scenarios in the absence of blockchain (off-chain mode) using the parameters from a uniform distribution shown in Table 4.1. In the next step, we intervene with consensus in the blockchain on the level of trust between banks and test the three scenarios again (on-chain mode). To investigate the number of simulations required to smooth out irregularities, we apply the convergence of subsequent mean values at the aggregation level by forming a moving mean value. As soon as the deviation of the calculated mean value from the convergence mean value is less than 0.05, we consider it to be robust. Although 40 simulations on average are enough to reach a robust mean, we only run each simulation ten times because of time constraints. Finally, we compare the average of results of these six experiments.

Table 4.1. Parameters for different economic cycles. This table lists the parameters expressing the uncertainty in different economic conditions for use in the simulation.

Parameter	Growth	Decline	Recession
noise of credits and lending	$\mathcal{U}(0,0.005)$	$\mathcal{U}(0.05,0.1)$	$\mathcal{U}(0.1,0.25)$
noise of deposits and payments	$\mathcal{U}(0,0.003)$	$\mathcal{U}(0.03,0.06)$	$\mathcal{U}(0.06,0.15)$

Each of these setups assumes that banks face an abundance or lack of liquidity with specific dynamics. The values of the other parameters used in our study are the same for all scenarios and are according to the coefficients and minimums set in Basel III and enforced by the ECB.

4.4.2 Experiments

Due to the limited hardware resources for simultaneous allocation to the blockchain network nodes, we perform this simulation with 30 random banking agents of different sizes whose balance sheets are adjusted based on the characteristics of banks operating in the French interbank market. Each experiment is based on an independent draw of the initial network for interbank loans as well as the balance sheet amounts of different banks. All initial networks are formed based on an initial value of 3 as the number of each bank's counterparts. However, as the simulation progresses, it is possible for banks to make new relationships over time. In off-chain mode scenarios, the acceptance of the request by a new lender is $1 - \sigma_i$ likely but at a higher premium than what the other partners of that agent pay. In on-chain mode scenarios, condition $\theta_{i,j,t} + \tau_{i,t} > 4$ must be met for the request to be accepted by a new lender (see Section 4.2.2), and the interest rate will be subject to the same procedure as the agent's other counterparts.

Comparing the number of banks in both off-chain and on-chain modes during 350 days of activity in times of economic growth in Figure 4.4(a) shows the stability of banks throughout the period. This means that when uncertainty is low, banks meet each other's liquidity needs well, and no default or failure is observed. From Figure 4.4(b), as the economy grows, the total number of loans in 40% of days in the off-chain mode is in a position above the 'number of banks' line ($n = 30$). It seems that in this mode, the general tendency of the borrowing banks is to borrow from more partners, and most of the lending banks tend to diversify their loan portfolio and lend to more banks. Another possible reason for this could be the dual activity of some banks, which act as both the lender and borrower in one day. By the intervention of blockchain, this trend goes surprisingly below the line (100%), meaning that a higher level of trust is interpreted as having narrower yet a deeper relationships with peers.

A look at the starting points and progression trends of the failures in Figure 4.4(a) provides a similar comparison for the economic decline situation. The simulation

results of the employed consensus algorithm to build trust among market members show that although the use of blockchain to realize this algorithm cannot ultimately prevent cascades of banks' failure, they can delay the collapse at least for a considerable time (89 days). During a recession, this opportunity is reduced to 45 business days. This means that the impact of using blockchain in restoring trust in the market during an economic decline is almost twice as great as during a recession. According to the almost uniform distance between the two on-chain diagrams in these two states in Figure 4.4(a), it seems that this is more affected by the severity of uncertainty caused by the economic situation than due to the blockchain features.

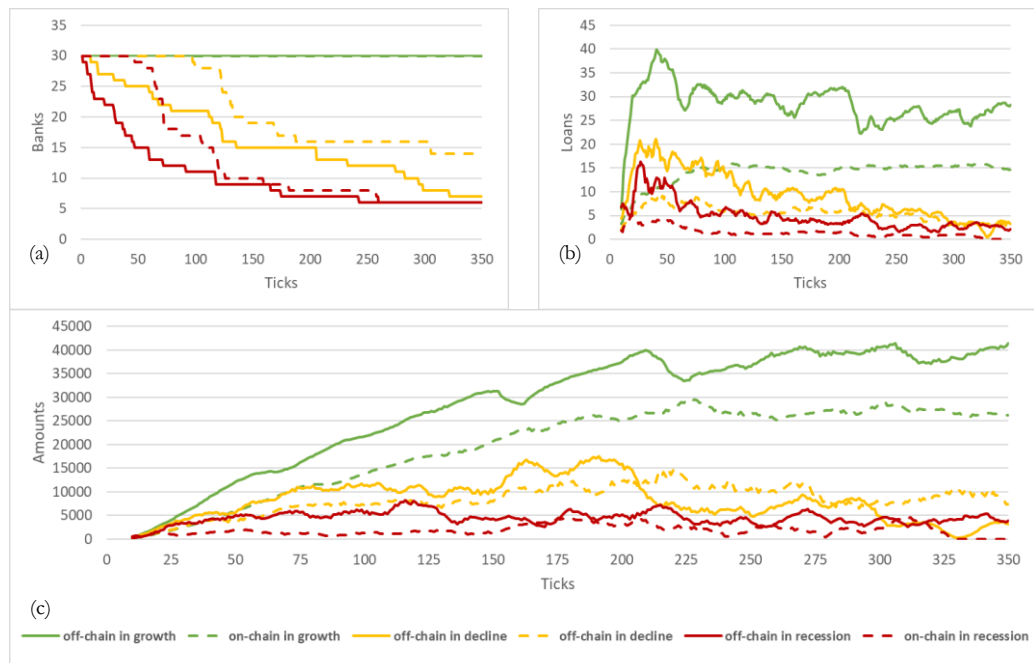


Figure 4.4. Evolution of (a) active banks, (b) the number of interbank loans, and (c) total amount of interbank loans in times of different economic situations: off-chain vs. on-chain modes. Subfigures (a), (b), and (c) display the number of active banks (i.e. not failed), interbank loans granted to both counterpart and non-counterpart banks, and total amount of funds exchanged through interbank loans, respectively, in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

Similar to economic growth scenarios, there are significant gaps between off-chain and on-chain modes in both the number and the total amount of loans in times of economic decline and recession (see Figure 4.4(b) and Figure 4.4(c)). It means that if

the blockchain is used in an unstable economic situation, both parties would prefer to reduce the number of agreements and increase the amount instead (i.e. trustworthy relationships). The gap between the number of loans in these two modes remains almost constant.

4.5 CONCLUSION AND FUTURE WORK

This paper presents a multi-agent simulation platform for the interbank market and integrates the notion of trust using a blockchain-based consensus algorithm to explore dynamics of lending relationships and the effects of uncertainty caused by different economic conditions. In order to compensate for the lack of liquidity of their peers, banks lend each other overnight. Unlike Khalid et al. (2021), we do not publish information on inter-agent agreements in the blockchain. Instead, we ask endorsing nodes in the network to determine how reliable is the borrower based on their previous track records, and finally to validate the transaction through a voting mechanism.

Based on the simulation results, the banking network remains stable during periods of economic growth without any additional need for a mechanism to strengthen trust. The issue of which of these two strategies in times of economic growth leads to lower cost and more operational advantage for the system and members can be the subject of new research. However, by increasing the uncertainty caused by changes in economic conditions, the establishment of a blockchain-based consensus mechanism in the market can help maintain trust between banks and, consequently, system stability (i.e. continuation of the presence of agents in the system). Although such a mechanism is not able to fully protect the market from contagious failures in the long run, it undermines the destructive effects of uncertainty for a significant period. An important point for the regulator and market participants is that since blockchain is an important factor in ensuring market resilience, the resiliency of the blockchain infrastructure should also be taken into account in times of stress so that it can meet expectations.

Good and bad history kept by the agents in our model can be interpreted as belief and disbelief (Cheng et al. 2021). Also, because uncertainty is considered as a parameter affecting the agents' behavior, we are interested in combining our method with the method of Cheng et al. (2021), which basically uses these items in calculating trust. As a limitation of our model, banks' decisions about lending, like other events outside their control, have a stochastic basis. Another future research direction is adding learning algorithms to the model so that agents make decisions based on their current and future goals, use what they learn from the past, and consider other agents' behavior. Maintaining trust between agents can be one of the goals to which they apply what they learn in using blockchain to conduct more trustful transactions in the future. Furthermore, the results do not model the case of a black swan event that could be the cause of a systemic collapse. A scenario in which economic growth is abruptly followed by recession can be of interest to scholars and practitioners to simulate and analyze the market in off-chain and on-chain modes.

5 TEST: A MAXIMAL MODEL

THE EFFECT OF DISTRIBUTED TRUST RESULTING FROM A BLOCKCHAIN CONSENSUS ALGORITHM ON INTERBANK MARKET STABILITY¹²

Abstract. Considering uncertainty in banks' liquidity needs as a proxy of trust in the interbank market, this paper proposes a blockchain consensus algorithm to build trust among the market players and uses an agent-based model to investigate the effects on market stability. We connect 413 heterogeneous banks in France that share liquidity through unsecured overnight loans and follow a standard set of interbank rules under Basel III. For three different economic scenarios (growth, decline, and recession), represented by three different levels of uncertainty, we study the impacts of off-chain and on-chain strategies on the banks' failures and the banking system's stability. This study shows that the use of blockchain to restore trust in the market helps to increase financial stability by delaying the cascade of failures. This delay would be a golden opportunity for the regulator to adopt new policies and save the market.

¹² This paper has been presented in the 3rd international conference on Digital, Innovation, Entrepreneurship & Financing (DIF2021–2022). Reference as: Alaeddini, M. (2022). The Effect of Distributed Trust Resulting from a Blockchain Consensus Algorithm on Interbank Market Stability. In *3rd international conference on Digital, Innovation, Entrepreneurship & Financing (DIF)*, Lyon, France.

Keywords. Asymmetric information; Default spread; Distributed ledger; Interbank call money market; Multi-agent simulation (MAS); Uncertainty

5.1 INTRODUCTION

An interbank money market (IMM), as a highly stochastic economic environment (Mitja Steinbacher and Jagrič 2020), is an official country-level or international market where banks lend large amounts of money to each other at interbank rates when they need liquidity in a short period. Banks adapt to this stochastic environment by exchanging interbank funds. For example, when clients withdraw their deposits from a bank, the bank may lack liquidity, leading to borrowing from other banks. Unsecured loans are usually granted for brief periods (e.g. one day), mainly based on the trusting relationship between the lender and the borrower and their previous loan history (Affinito 2012, Iori et al. 2015, Temizsoy et al. 2015, Kobayashi and Takaguchi 2018).

Today, many unsecured loans are verbally agreed upon and granted to partners through recurring loans (Renard 2017). Establishing more lending relationships in the IMM helps borrowers with more diverse sources of liquidity (Ben R. Craig et al. 2015) and enables them to borrow at lower interest rates from lenders with whom they have a relationship (Cocco et al. 2009). However, these relationships dynamically change due to the short-term nature of unsecured funding (Anand et al. 2012). In order to maintain credit relationships, maintaining a level of trust is essential for all market participants, as its evaporation can lead to instability (Temizsoy et al. 2015, T. Xu et al. 2016a) and liquidity crises (Heider et al. 2009, Acharya and Merrouche 2013).

Lack of liquidity in the market can affect lending relationships and gradually create a crisis. Increasing demand for liquidity in the market raises interest rates (Taylor and Williams 2009), which, along with increasing client withdrawals, will weaken the situation of debtor banks. In such circumstances, it is very likely that some banks with excess liquidity refuse to lend for fear of their counterparts' insolvency and loss of their capital (Aldasoro et al. 2017, Serri et al. 2017). They may also provide liquidity to the

applicant banks against high-liquid securities as collateral (Barroso et al. 2016). These difficulties in compensating for the lack of liquidity may lead to the default of some debtor banks and, ultimately, their failure (Taylor and Williams 2009, Barroso et al. 2016). The financial crisis of 2007–2008 is a good example of considering the interrelationships between liquidity and the ability of financial institutions to pay off debts and proving the critical role of the IMM in the economy (Adrian 2015). In fact, the interbank market suddenly dried up while banks were in dire need of liquidity to make up for their shortfalls as the crisis unfolded.

What is clear is that positive or negative economic growth has a significant impact on confidence in financial markets, especially in the interbank market (Zak and Knack 2001, Beugelsdijk et al. 2004, Degryse et al. 2019). On the one hand, conventional monetary policies are often unsuccessful in restoring trust in the IMM and solving the liquidity crisis induced by a confidence shock (Ferrari 2020). On the other hand, due to the readvent of the notion of distributed trust (Abdul-Rahman and Hailes 1998) through the use of blockchain (Hawlitschek et al. 2018, Veloso et al. 2019, Bellini et al. 2020), this technology is widely believed to address all three vital, formal mechanisms of economic confidence (i.e. information, contract, and regulation (Tonkiss 2009)). Examining whether blockchain, as a cryptographically secured, distributed ledger, is able to compensate for the loss of confidence during economic declines is our main motivation for doing this research. Therefore, the two main questions to be answered in this research are: (i) What effect do different levels of uncertainty as a proxy for trust (Dequech 2005, Loizos 2020) have on the banking system's stability in different economic situations? (ii) Can the use of blockchain to increase market confidence increase stability in times of diminished trust?

Concretely, the contributions of this paper are twofold: (i) adding to the literature on interbank trust and (ii) using blockchain abstraction as part of the simulation platform. To these aims, Section 5.2 gives background information about the mutual effects of trust and IMM stability on each other and what can be expected from blockchain in this regard. Section 4.3 describes the developed model for this study, including the overnight lending and pay-off processes and the behavior of various

agents in different circumstances. The results of simulating this model based on the three mentioned scenarios are presented in Section 4.4. Finally, Section 5.5 concludes the paper and gives future works.

5.2 BACKGROUND

5.2.1 The Interrelationship between Trust and the IMM

Above all, market shocks caused by financial crises affect lending relationships and consequently change the market structure. According to Abbassi et al. (2015), the dispersion of different lenders' offered prices on unsecured overnight loans increases sharply with the crisis. Relationship lenders do not consider previous lending relationships and charge higher prices for identical contracts, especially for riskier borrowers. Hatzopoulos et al. (2015) show that in times of crisis, despite the large volume of preferential transactions, the number of trades decreases, and transactions occur at higher interest rates than before the crisis, meaning that the trustworthy relationships relatively increase. In contrast, many untrustworthy relationships disappear. This conclusion is entirely consistent with the events of the global financial crisis of 2007–2008, where, although relationship lenders played a key role as liquidity providers, they nevertheless forced borrowers to pay premiums for transactions (Liberati et al. 2015, Temizsoy et al. 2015). This is also confirmed by Kobayashi and Takaguchi (2018), who found that relationship lenders tend to impose higher interest rates on borrowers in times of financial distress.

Part of the literature in this area focuses specifically on the trust arising from previous relationships between the lender and the borrower and reveals its effects on future lending. Finger and Lux (2017) show that the impact of past transactions plays an essential role in shaping trust between banks and sustaining many aspects of their behavior in managing their lending relationships, especially in times of crisis. Affinito

(2012) finds by studying the Italian IMM that borrowers were selected based on their pre-existing relationships during the global financial crisis of 2007–2008. Iori et al. (2015) stress the importance of lenders' memory in their lending decisions and show that a lender who has lent a lot to a borrower in the past will lend to it more readily in the future than to new borrowers or those who have rarely borrowed. Furthermore, Temizsoy et al. (2015) confirm that borrowers with older relationships have access to larger volumes of overnight loans. Similar statements are abundant in the literature in this field (e.g. Kobayashi and Takaguchi (2018), Liu et al. (2018), Degryse et al. (2019)).

Scholars have also researched the effects of lack of trust in the IMM on its stability. Banks' strategy of diversifying or conditioning their lending relationships is entirely influenced by their trust in their counterparts and the market as a whole and ultimately affects network stability (Gabrieli and Georg 2014, Bräuning and Fecht 2017). In fact, fluctuations in the level of mutual trust between banks make it possible to share risk between various parties to the loan and even nullify capital regulations (Loizos 2020). The severity of these effects is such that the spread of distrust in the IMM and the continuation of the trust crisis can cause major shocks to the market and even lead to a liquidity crisis (Heider et al. 2009, Acharya and Merrouche 2013, Bülbül 2013, Ferrari 2020) – the factors that are themselves the main causes of systemic failures and extreme instability in the market (Caccioli et al. 2015, Siebenbrunner 2020).

The closest work to our study has been by Mitja Steinbacher and Jagrič (2020). They examine nine different scenarios that multiply three situations for economic growth (i.e. growth, decline, and stagnation) by three levels of uncertainty (i.e. no, moderate, and high uncertainty) in a hypothetical interbank market. Therefore, our research continues that work to examine the impact of the economic downturn on the IMM. The differences are: (i) Our model is more complex in terms of supporting various processes in the overnight loan market and the behavior of different market members; (ii) Instead of using a hypothetical IMM, we attempt to simulate a real IMM based on the French aggregate balance sheet data; (iii) We look at uncertainty as a proxy for IMM confidence.

5.2.2 Distributed Trust through Blockchain, Smart Contracts, and Consensus

Although the notion of distributed trust dates back to the late 1990s (Abdul-Rahman and Hailes 1998), there was no comprehensive solution that could make it easily accessible until the advent of blockchain technology and its popularity in recent years. By using blockchain, it is easier to implement previous ideas in the fields of distributed trust and trust-free networks (Hawlitschek et al. 2018). A blockchain refers to a cryptographically secured distributed ledger with a decentralized consensus mechanism (Risius and Spohrer 2017). More precisely, it is an immutable, append-only data structure of transactions organized as a list of blocks cryptographically linked to other nodes in a peer-to-peer network. A blockchain can manage self-enforcing agreements embedded in computer code called smart contracts. The smart contract code contains a set of rules under which the parties agree to transact with each other. A consensus must be reached between a certain number of network nodes about a transaction to finalize it.

Due to the high degree of ecosystem closure that peer-to-peer markets typically offer, the blockchain can be a viable option for decentralizing intermediary services and eliminating mistrust (Glaser 2017). As trust is an essential prerequisite for all market players to adopt a blockchain-based system in their day-to-day operations (Sas and Khairuddin 2015), the need for trust in the IMM cannot be wholly eliminated. However, it can be shifted from the central authorities to the algorithmic logic, i.e. the formal and legal validity of the underlying smart contracts in the blockchain (Greiner and Wang 2015, Al Khalil et al. 2017). Therefore, a smart contract's understandability and integrity over time, as well as the absence of unilaterally manipulable data, are prerequisites for distributed trust (Fröwis and Böhme 2017).

To the best of our knowledge, there are few studies on the application of blockchain in IMM. Guo and Liang (2016) mention a number of standardizations by various associations and countries regarding the use of blockchain in the IMM. Cucari et al. (2021) discuss a case study of the Spunta project in the Italian banking sector and

argue how the project uses blockchain to create greater transparency and visibility, faster execution, and the ability to transfer checks and money directly within the IMM. Among these studies, only Alaeddini et al. (2021) go beyond generalizations and consider blockchain an innovative component in designing a modern multi-agent IMM system that can support both secured and unsecured loan scenarios. Although trust is considered a significant concern in their work, their idea of a blockchain-based IMM remains at the design level, as no implementation of this architecture has been provided. Therefore, our research can be considered a continuation of that study to realize a part of a blockchain-based interbank market.

5.3 THE MODEL

In an extensive financial market network, where each node represents several market operations, many entities interact non-linearly with each other, making it a complex system. Undoubtedly, IMM is one of the most complex systems in banking and monetary policy (Alaeddini et al. 2021). The multiplicity of actors with constantly changing roles from lender to borrower and vice versa, especially when the central bank intervenes in the market as a lender of last resort, along with the variety of lending methods, are the primary reasons for the complexity. Another complexity emerges in supporting the market participants' main concerns and their impact on the banks' goals and decisions to supply and demand liquidity (Alaeddini et al. 2021).

A way to reduce the complexity of a system with mentioned specifications could be to use self-organizing agent-based modeling (ABM) (Haber 2010). ABM provides a computational representation of a set of micro-entities (i.e. agents) interacting with each other and changing over time that form a macro-system (Epstein and Axtell 1996, Grimm and Railsback 2012). Each agent in the model is characterized by specific attributes (e.g. size and equity) and behaviors (e.g. lending and borrowing). As a bottom-up approach, ABM makes it possible to discover individual behaviors and causal mechanisms that lead to macro-level phenomena (McAlpine et al. 2020).

5.3.1 The IMM's Logic

The model builds on a number of recent studies (Sato et al. 2019, Teply and Klinger 2019, Popoyan et al. 2020, Mitja Steinbacher and Jagrič 2020) and is populated by two types of agents: (i) N banks that interact with and lend to each other, and (ii) one central bank that regulates the market and helps banks avoid failure when necessary. Furthermore, an unsecured lending contract has been developed to support interactions among the agents. The general logic of the simulation is that banks manage their liquidity by exchanging funds in the IMM. The matching of liquidity in the IMM is managed by a central clearing counterparty (i.e. the central bank), and all interbank payments are simulated to be made in the blockchain.

Banks are heterogeneous, imperfect, autonomous, and to some degree adaptive agents. They follow base-level rules to make interbank placements and must meet all regulatory requirements in their transactions and changes in their balance sheets. The natural and financial sides of the market are linked by multiple, non-linear feedbacks and evolve in a finite time horizon, indexed by $t = 1, 2, \dots, T$. Each period corresponds to a day.

5.3.1.1 Banks' Balance Sheet

Table 5.1 summarizes the elementary balance sheet operations in the model. These operations consist of loanable funds, financial assets and liabilities, deposits, and reserve balances as well as other assets and liabilities. Adapted from Teply and Klinger (2019), we rely on proxy data inferred from the European Central Bank (ECB) (ECB 2021b, 2021a) to approximate the interbank network as close to the real world as possible. This model focuses on data from French banks and approximates banks based on related parameters such as total assets and banking sector structure, number of banks, and market concentration in France. High-level aggregate data on banking systems approximate the structure of the IMM according to the positions reported to the Bank of International Settlements (BIS 2009).

Because banks are different in size, in our model, we introduce three sizes of small, medium, and large banks with a market share of 15%, 25%, and 60%, respectively, due to the medium concentration of the French IMM (Teply and Klinger 2019). The total assets in the aggregate balance sheet of French banks amount to € 10,776.3 billion at the end of the last quarter of 2020 (ECB 2021b), which is allocated to 413 banks (ACPR 2021) in different sizes at the mentioned percentages. For this purpose, according to Mitja Steinbacher and Jagrič (2020), we use the normal distribution with a noise of 0.2. The amounts of different operations in each bank's balance sheet are calculated based on the above values and the illustrative percentages of balance sheets of the small, medium, and large banks, shown in Table 5.1.

Table 5.1. Illustrative, stylized balance sheet for small, medium, and large banks. This table lists the operations of banks' balance sheets as well as the share of small, medium, and large banks in the aggregate balance sheet.

Total assets (A)	Total liabilities (L)
Securities (s): 10,8,5% ^a	Equity (e): 13,9,4%
Clients' credits (c): 33,36,30%	Clients' term deposits (d): 16,16,14%
Interbank claims (i): 9,18,45%	Clients' demand deposits (d'): 16,16,14%
Cash and central bank deposit (r): 8,4,4%	Interbank funds (b): 8,16,40%
Other assets (A'): 40,35,16%	Central bank funds (f): 0,0,0%
	Other liabilities (L'): 46,43,27%
Securities pledged for the CB funds (s'): 0,0,0%	

^a The values are respectively related to small, medium, and large banks

The initiation stage in our model determines the balance sheet of each bank and includes the following steps. The next stages of simulation and experiment with different scenarios are done using the balance sheets obtained from this stage.

1. Create banks.
2. Create the central bank.

3. Create random counterparts for banks and assign their initial assets and liabilities according to banks' sizes. The initial IMM network is formed by setting 20 as the initial value of the number of each bank's counterparts.

To study the behavior of banks regarding the application and approval of interbank credits and the establishment and maintenance of the interbank network on this basis, it is assumed that at first there are no interbank loans to be repaid by banks (none of the banks owes to other banks).

5.3.1.2 Time Value of Assets and Liabilities

Let each bank i in the model be given, at time step t , the values of financial assets $s_{i,t}$, loans to the real economy $c_{i,t}$, loans to other banks $l_{i,t}$, short-term reserve $r_{i,t}$, real economy deposits (i.e. term deposits $d_{i,t}$ and demand deposits $d'_{i,t}$), debts to other banks $b_{i,t}$ and to the central bank $f_{i,t}$ as well as its capital $e_{i,t}$. Other assets and liabilities of bank i are denoted by $A'_{i,t}$ and $L'_{i,t}$. Central bank funds are granted against part of the bank's securities denoted by $s'_{i,t}$.

According to Mitja Steinbacher and Jagrič (2020), intertemporal changes in $d_{i,t}$ and $c_{i,t}$ follow Gaussian random walks with related moving drifts $\mu_{d_{i,t-1}}$ and $\mu_{c_{i,t-1}}$, respectively, and noises σ_{d_i} and σ_{c_i} . We use a similar mechanism to update bank i 's other assets and liabilities using moving drift $\mu_{al_{i,t-1}}$ and noise σ_{al_i} . Also, in addition to the effect of the customer loans principal on the demand deposits $d'_{i,t}$ (i.e. money creation), it changes through the central bank's settlement process as the difference between bank i 's payments to other banks and the payments of other banks to bank i . For this purpose, total payments of bank i to other banks per day (i.e. total withdrawals from demand deposits), $p_{i,t}$, follows a Gaussian random walk with moving drift $\mu_{p_{i,t-1}}$ and noise σ_{p_i} . In 2020, the total value of cashless payments in France via credit

transfers, direct debits, and checks was € 35,010.4 billion¹³. This means an average of € 95.9 billion per day, which is equivalent to 0.9% of the total assets of French banks – that is used in the model to simulate the first round. It is worth noting that profit received on facilities and interest paid on deposits affect capital $e_{i,t}$, while at the maturity of time deposits, the principal affects cash $r_{i,t}$.

At the end-of-day, in case of liquidity deficit, when bank i borrows from bank j in the IMM, $r_{i,t}$ and $b_{i,t}$ increase by the amount of the loan, while equally, $r_{j,t}$ decreases and $l_{j,t}$ increases. It is worth noting that bank j must comply with Basel III rules on lending (Equations 3 and 4). When bank i repays its debt to bank j , both values of $r_{i,t}$ and $r_{j,t}$ will change oppositely. Banks i and j apply an interest paid on loan and a profit obtained from the loan in their equity (i.e. $e_{i,t}$ and $e_{j,t}$). The principal amount of the loan is also deducted from $b_{i,t}$ and $l_{j,t}$. If the central bank refinances bank i , the amount changes all the values $r_{i,t}$, $f_{i,t}$, $s_{i,t}$, and $s'_{i,t}$, while repayment of central bank debt is applied in reverse. As long as the ratio of securities to total assets is maintained, banks can devote part of their liquidity surplus to investing in securities. The purchase of securities affects $r_{i,t}$ and $s_{i,t}$.

In the model, if a bank cannot repay its debt, it becomes insolvent and bankrupt. In this case, the bank has to sell its assets below market prices to pay its unpaid debts. The total liquidity that the bank earns from the fire sale is equal to:

$$FS_{i,t} = (1 - \lambda_{s_{i,t}})\varphi_{s_{i,t}}s_{i,t} + (1 - \lambda_{c_{i,t}})\varphi_{c_{i,t}}c_{i,t} \quad (1)$$

where $\lambda_{s_{i,t}}$ and $\lambda_{c_{i,t}}$ denote loss coefficients of fire selling securities and facilities by bank i in time step t , and $\varphi_{s_{i,t}}$ and $\varphi_{c_{i,t}}$ denote the quantity sold of each asset.

¹³ <https://www.statista.com/statistics/1110685/value-cashless-payment-by-type-payment-service-france>

Consequently, the total loss from the fire sale of assets is calculated as follows:

$$LF_{i,t} = \lambda_{s_{i,t}} \varphi_{s_{i,t}} s_{i,t} + \lambda_{c_{i,t}} \varphi_{c_{i,t}} c_{i,t} \quad (2)$$

In terms of accounting, the amount of $r_{i,t}$ increases by the amount of $FS_{i,t}$, and the amount of $e_{i,t}$ decreases by the amount of $LF_{i,t}$. Values $s_{i,t}$ and $c_{i,t}$ are also affected by the amount of securities and facilities sold, respectively.

If the bank fails to make up for its liquidity deficit or if its equity is zero or less, it has to raise equity in order to stay in the market. In our model, with a 50% probability, banks will increase their capital due to their lack of liquidity; otherwise, they will fail. The increase in capital changes $r_{i,t}$ and $e_{i,t}$. In the case of failure, it also leads to losses resulting from the bank's zero debt to the banks from whom it has borrowed. It means reducing values $l_{j,t}$ and $e_{j,t}$ by the amount of defaulted debt of bank i to bank j . This is the unique source of contagion in our model.

5.3.1.3 Compliance with Regulations

To achieve compliance with Basel III, the value of $c_{i,t}$ should not be greater than either the regulatory ceiling ($RC_{i,t}$) or the leveraged limit ($LL_{i,t}$) of the loan, which are calculated as follows:

$$RC_{i,t} = \frac{1}{\epsilon} e_{i,t-1} - (\omega_c c_{i,t-1} + \omega_l l_{i,t-1}) \quad (3)$$

$$LL_{i,t} = \frac{1}{\alpha} e_{i,t-1} - (s_{i,t-1} + l_{i,t-1} + r_{i,t-1}) \quad (4)$$

where ϵ denotes the minimum capital adequacy requirement, and α denotes the leverage requirement. Also, risk-weights for commercial loans and interbank loans are denoted by ω_c and ω_l , respectively.

In order to manage liquidity $r_{i,t}$ and calculations related to its excess or deficit, banks are required to provide a reserve including at least a minimum requirement specified by the central bank and a capital buffer (π) following Basel III. Also, the liquidity coverage ratio ($LCR_{i,t}$) must be considered by banks in calculating surplus or lack of liquidity. The primary purpose of the $LCR_{i,t}$ is to enhance liquidity resilience by forcing banks to hold sufficient high-quality liquid assets ($HQLA_{i,t}$) to withstand the stress scenario of net cash outflows ($NCOF_{i,t}$) over four weeks. In Basel III, the minimum value of the liquidity coverage ratio ($\bar{\rho}$) must be set to 1, meaning that the level of high-quality assets must fully cover the level of net expected cash flows:

$$LCR_{i,t} = \frac{HQLA_{i,t}}{NCOF_{i,t}} \geq \bar{\rho} \quad (5)$$

here $HQLA_{i,t}$ and $NCOF_{i,t}$ are calculated as follows:

$$HQLA_{i,t} = r_{i,t} + s_{i,t} + \min \left[0.85l_{i,t}, \frac{2}{3}(r_{i,t} + s_{i,t}) \right] \quad (6)$$

$$NCOF_{i,t} = XF_{i,t}^- - \min[XF_{i,t}^+, 0.75XF_{i,t}^-] \quad (7)$$

As seen from Equation 6, following Basel III, we consider levels 1 and 2 high-quality liquid assets in calculating the liquidity coverage ratio. Adapted from Popoyan et al. (2020), in our model, level 1 assets include cash $r_{i,t}$ and securities $s_{i,t}$, while level 2 assets include interbank loans $l_{i,t}$, which can contribute to $HQLA_{i,t}$ with a haircut of 15% of their value and up to two-thirds of the value of level 1 assets. Also, in Equation 7, $XF_{i,t}^-$ and $XF_{i,t}^+$ denote the expected cash outflows and inflows, respectively, which will be calculated using the current contractual cash outflows ($CF_{i,t}^-$) and inflows ($CF_{i,t}^+$) as follows:

$$XF_{i,t}^- = CF_{i,t}^- + \sum \vartheta_L L_{i,t} = CF_{i,t}^- + \vartheta_D(d_{i,t} + d'_{i,t}) + \vartheta_{CB}f_{i,t} + \vartheta_{IB}(b_{i,t} - l_{i,t}) \quad (8)$$

$$XF_{i,t}^+ = CF_{i,t}^+ - \sum \vartheta_A A_{i,t} = CF_{i,t}^+ - (\vartheta_C c_{i,t} + \vartheta_R r_{i,t} + \vartheta_S s_{i,t}) \quad (9)$$

where according to Basel III, $\vartheta_D = 0.1$, $\vartheta_{CB} = 0.25$, and $\vartheta_{IB} = 1$ are the run-off rates of liabilities, and $\vartheta_C = 0.5$, $\vartheta_R = 0$, and $\vartheta_S = 0.2$ are the default rates of assets. Also, current contractual cash outflows ($CF_{i,t}^-$) and inflows ($CF_{i,t}^+$) are respectively obtained from the difference between current and previous liabilities and between current and previous assets.

Accordingly, the amount of liquidity excess ($Liq_{i,t}^{exc}$) or deficit ($Liq_{i,t}^{def}$) would be calculated through the following equations:

$$Liq_{i,t}^{exc} = \begin{cases} \frac{1}{\bar{\rho}} HQLA_{i,t} - NCOF_{i,t}, & \text{if } LCR_{i,t} > \bar{\rho} \\ 0, & \text{if } LCR_{i,t} \leq \bar{\rho} \end{cases} \quad (10)$$

$$Liq_{i,t}^{def} = \begin{cases} \bar{\rho} NCOF_{i,t} - HQLA_{i,t}, & \text{if } LCR_{i,t} < \bar{\rho} \\ 0, & \text{if } LCR_{i,t} \geq \bar{\rho} \end{cases} \quad (11)$$

5.3.2 Agents' Behavior

Describing the primary process of the modeled IMM as a sequence of interactions between agents facilitates the introduction of model elements and the validation of model design and serves as a starting point for testing the model. In every period t , the following sequence of events takes place:

1. The values of the balance sheet of the last period are stored.
2. Clients' term deposits are updated.
3. Clients' credits are updated. Banks must comply with both the capital adequacy ratio and the leverage ratio on loans.
4. Banks update the payments of their clients by changing the amounts of demand deposits. The central bank makes a clearing matrix for interbank payments.

5. Banks use their reserve balance to settle their clearing vector.
6. Banks update their other assets and liabilities.
7. Banks repay their matured interbank debts by their cash and reserve balance.
 - a. Banks that do not have sufficient reserves to repay their debts, if they have credit receivable on the current day, which is due to the repayment of other banks' debts, wait until the successive settlement cycles on the current day.
 - b. Banks that do not have enough reserves and receivables repay their debts by borrowing first from other counterparts and then from other banks (see step 10 for more details).
 - c. Lending banks evaluate their counterparts.
8. Banks calculate their liquidity excess or deficit. They must comply with the liquidity coverage ratio on their surplus. Then banks provision their reserve.
9. Banks that have excess liquidity pay part of the surplus to buy securities. They must comply with the authorized limit for the purchase of securities.
10. In order to manage their liquidity and based on the required reserve and counterparts' history, banks borrow or lend in the market. For this purpose:
 - a. Borrowing banks send their loan requests first to their lending counterparts based on their history.

- i. Lending partners respond to requests based on their excess, formulated on the liquidity coverage ratio, and borrowing banks' good history.
 - ii. They must also comply with both the capital adequacy and the leverage ratios on loans.
 - b. If banks cannot borrow from their existing counterparts, they will apply for a loan from other banks with lending position in the network. In our model, smaller banks first send their loan request to larger banks and vice versa (Cocco et al. 2009, Affinito 2012, Fricke and Lux 2015, T.C. Silva et al. 2016).
 - i. If lending banks are able to meet all or part of the liquidity needs of the applicant banks, they adopt two different strategies against the two off-chain (traditional) and on-chain (blockchain-based) modes (see Section 5.4).
 - ii. In either case, both borrowing and lending banks add each other to their counterparty list if the loan is granted.
 - c. Borrowing banks evaluate their counterparts.
 - d. Once again, after making up, banks try to repay their overdue loans, if relevant.
11. Banks repay their central bank debt with the rest of their liquidity surplus.
12. Banks that have not been able to make up for their need in the market will be refinanced by the central bank if they have enough securities. Then, banks try to repay their overdue loans, if relevant.

13. Banks that cannot make up for their lack of liquidity, either through interbank loans or central bank refinancing, will have to fire sell. Then, banks try to repay their overdue loans, if relevant.
14. At the end-of-day, the position of banks are determined.
15. At the end-of-day, a bank goes bankrupt if it fails to make up for its liquidity deficit or its equity is zero or less and does not compensate for these problems by raising its equity. The bank's bankruptcy also leads to losses resulting from its zero debt to the banks from whom it has borrowed.

5.3.3 Quantification of Uncertainty in the IMM

This study considers the uncertainty associated with model predictions because ignoring it means ignoring reality. The inclusion of uncertainty in the model's input parameters and its use in simulation can help quantify the uncertainty in the resulting model predictions (i.e. the model output) (Loucks and Van Beek 2017). Banks operate in an environment of change and uncertainty. On the one hand, liquidity suppliers are always uncertain, and on the other hand, liquidity demand is constantly changing, and these changes cannot always be predicted (González et al. 2014). Many of the parameter values of interest rate forecasting models are also changing and uncertain (Altavilla et al. 2019). Although the models used to predict these values are primarily based on many inaccurate assumptions, planning and managing the IMM's supply and demand cannot be avoided despite this uncertainty.

We incorporate some of this uncertainty into our model to the extent that probabilities can be assigned to parameter values. More specifically, we use a stochastic approach for modeling random events that occur over time and provide alternative time series of outputs with their probabilities. Random variables in our model mainly include balance sheet operations related to banks' clients. Increasing or decreasing the values of term deposits (by deposit or withdrawal), demand deposits (mainly through

interbank payments), and client credits are all random events in our model. Also, the decrease and increase of other assets and liabilities of banks in our model are random. To produce these random values, we employ Gaussian process modeling using normal distributions with the moving average of past values and a variance commensurate with the economic situation obtained from the literature in this field.

5.3.4 Formulation of Trust Using Blockchain

As can be seen from the previous sections, the trust that we address in the form of uncertainty modeling is more focused on the general trust of the society in the banking system, whose impact can be seen in clients' deposits/withdrawals and interbank payments as well as banks' investment in client loans. This section proposes a mechanism for calculating, documenting, and informing trust among members using a blockchain consensus method. Our ultimate goal is to simulate the effects of this solution on market stability and to examine whether making such a change can prevent the loss of market confidence in times of crisis.

The issue of trust in the IMM and its determinants have been addressed by some researchers. Li et al. (2010) use a trust vector to form their simulated IMM but do not specify any criteria for determining the elements of this vector and only use the normal distribution to generate a series of random numbers (i.e. trust values). Liff and Wahlström (2017) found through several qualitative interviews with bank executives that, in normal times, formal information about the ability and integrity of counterparts can build weak trust. In contrast, in order to be able to trust a bank in a financial crisis, benevolence must already be established between the peers (strong trust). They also do not provide specific criteria for calculating the value of trust between banks. Using a similar qualitative method, Rad (2017) provides high-level criteria, such as guaranteed banks and clan-related banks, for selecting a trust-based partner in the IMM and addresses issues such as negative expectations, goodwill, and information sharing as trust-based performance-control processes regarding the selected counterparts. Del Prete and Federico (2019) use assets, liabilities, and guarantees among correspondent

banks in the IMM as trust measures in their study of whether financial crises affect trade flows via a shock to corporate risk or bank risk. To the best of our knowledge, among all the research conducted in this field, only Bülbül (2013) studies a number of measures for banks' trust in the IMM through quantitative research.

To address the issue of trust, we use a reputation system as an additional trust layer based on counterparts' relationships (Pazaitis et al. 2017), which enables banks to engage in decentralized, trusted IMM interactions on top of the 'trustless' blockchain technology. Adapted from Abdul-Rahman and Hailes (1998), we apply six values from -1 (distrust) to 4 (complete trust) for both direct and recommender classes of trust. The value of direct trust is the result of assessing the lender's trust in the borrower in a loan transaction, while a recommender is a communicated trust information, which contains reputation information. Agents use values of their direct trust in an agent – recorded in their databases – in order to arrive at a consensus on its reputation and recommend it to other agents. In our model, we use a voting-based consensus mechanism (G. Sun et al. 2020) (an often-used category of consensus algorithms in consortium blockchains (G.-T. Nguyen and Kim 2018, W. Yao et al. 2021)), in which the commitment depends on which committed result achieves the majority of votes.

5.3.4.1 Lenders' Expected Trust Level

We map our six values of trust to the six ordered levels of trust mentioned by Bülbül (2013). To find the most appropriate level of trust in banking networks, The author uses several determinants, including interaction with the central bank ($X_{1_{i,t}}$), equity ($X_{2_{i,t}}$), competitiveness ($X_{3_{i,t}}$), net interest income ($X_{4_{i,t}}$), and size ($X_{5_{i,t}}$) of bank i (Bülbül 2013) at time t . The variable $X_{1_{i,t}}$ is constructed as a dummy variable taking the value 1 for at least one active loan transaction with the central bank and 0 otherwise. The variable $X_{2_{i,t}}$ is the ratio of the bank's equity over total assets. Bank competition ($X_{3_{i,t}}$) in the market is estimated by the Lerner index, which is constructed

following Berger et al. (2017). The Lerner index, which shows the difference between prices and marginal cost by values between 0 and 1, is calculated as follows:

$$X_{3,i,t} = \frac{(P_{i,t} - MC_{i,t})}{P_{i,t}} \quad (12)$$

where $P_{i,t}$ is the price of total assets proxied by the ratio of total revenues to total assets for bank i at time t , and $MC_{i,t}$ is the marginal cost of total assets for bank i at time t . In order to calculate the marginal cost, the following translog cost function with one output (i.e. total assets, $A_{i,t}$) and three input prices (i.e. the price of labor, $W_{1,i,t}$; the price of capital, $W_{2,i,t}$; and the price of funding, $W_{3,i,t}$) should be estimated:

$$\begin{aligned} \ln TC_{i,t} = & \alpha_0 + \alpha_1 \ln A_{i,t} + \frac{1}{2} \alpha_2 (\ln A_{i,t})^2 + \sum_{m=1}^3 \beta_m \ln W_{m,i,t} \\ & + \sum_{m=1}^3 \sum_{n=1}^3 \beta_{m,n} \ln W_{m,i,t} \ln W_{n,i,t} + \sum_{m=1}^3 \gamma_m \ln A_{i,t} \ln W_{m,i,t} + \varepsilon \end{aligned} \quad (13)$$

The three prices of labor, capital, and funding are proxied by the three ratios of personnel expenses to the total asset, non-interest expenses to fixed assets, and interest paid on customer deposits and interbank funds to total deposits and funds. All these elements are extracted from the aggregate balance sheet of French banks reported by the ECB (see Section 5.3.1). Also, total cost, $TC_{i,t}$, is the sum of personnel expenses, non-interest expenses, and interest paid. The estimated coefficients of the cost function from Equation 13 are then used to derive the marginal cost:

$$MC_{i,t} = \frac{TC_{i,t}}{A_{i,t}} \left(\alpha_1 + \alpha_2 \ln A_{i,t} + \sum_{m=1}^3 \gamma_m \ln W_{m,i,t} \right) \quad (14)$$

Furthermore, the variable $X_{4,i,t}$ is calculated as the ratio of bank i 's net interest income over total income, while the logarithm of bank i 's total assets is a proxy for $X_{5,i,t}$.

Accordingly, the result of the calculations provides an estimate of the level of trust that a particular lender expects from the market (including a particular borrower). According to the ordered logit model (Williams 2016):

$$\tau_{i,t}^* = \sum_{k=1}^5 \beta_k X_{k,i,t} + \varepsilon_{i,t} \quad (15)$$

$$\tau_{i,t} = \begin{cases} -1, & \text{if } \tau_{i,t}^* \leq \kappa_1 \\ 0, & \text{if } \kappa_1 < \tau_{i,t}^* \leq \kappa_2 \\ \vdots & \\ 4, & \text{if } \tau_{i,t}^* > \kappa_5 \end{cases} \quad (16)$$

where $\tau_{i,t}$ denotes bank i 's trust threshold at time t (i.e. the observed ordinal variable mapped to the levels of trust), and $\tau_{i,t}^*$ is a continuous, unobserved latent dependent variable, whose values determine what the observed ordinal variable $\tau_{i,t}$ equals. A value of -1 means that bank i has no confidence in the market members, while a value of 4 means it has complete confidence in the market and the members who have the appropriate level of trust. The values β_k are the regression coefficients that we wish to estimate, $\varepsilon_{i,t}$ is the error term, and the parameters κ_1 to κ_5 are the externally imposed endpoints of the observable categories.

5.3.4.2 Borrowers' Trust Level

Let $\theta_{i,j,t}$ denote the trust level between banks i and j at time t . In general, a credit relationship between banks i and j at time t is allowed if $\theta_{i,j,t} + \tau_{i,t} > 4$, where bank i is the creditor, and bank j is the debtor. Typically, different banks may have different trust thresholds, so here we let $\tau_{i,t}$ fall between the interval of $[-1,4]$.

(a) The Level of Trust of an Old Counterpart

For the old counterparts, the level of direct trust between bank i and bank j at time t is obtained from the following formula:

$$\theta_{i,j,t} \approx \max \left[-1, \left(\frac{H_{i,j,t}^{good} - H_{i,j,t}^{bad}}{H_{i,j,t}} \times 4 \right) \right] \quad (17)$$

where $H_{i,j,t}^{good}$ indicates the history of good records of bank j in repaying the loans it has received from bank i until time t , and $H_{i,j,t}^{bad}$ denotes the history of bad records in the same period. $H_{i,j,t}$ also indicates the number of lending relationships between banks i and j from the beginning to time t .

(b) The Level of Trust of a New Counterpart

To calculate the level of indirect trust between two counterparts who did not have a credit relationship with each other before time t , we use a dynamic trust mechanism adapted from Walter et al. (2009) and an endorsement mechanism adapted from Alaeddini et al. (2021). In this method, each bank determines its counterparts' trust level using Equation 17 when recording their loan repayment transactions in the blockchain. Whenever a bank wants to lend to a new bank with which it has not had a credit relationship, it asks endorsers to examine the level of trust of this new counterpart. Endorsers, which are nodes located in the credit paths leading to the endorsee node, calculate its trust level by tracking the points assigned to that node and their credit paths that lead to it. The final score, subject to consensus, would be obtained based on the recommendations of other related nodes before the time of the loan transaction.

We define the indirect trust of bank i to bank j as the direct/indirect trust of the counterparts k of bank i to bank j , weighted by the trust of bank i towards these neighbor agents k . Let $w_{i,j,t}$ denote the elements of the stochastic matrix for normalizing the values of $\theta_{i,j,t}$ (the value of $\theta_{i,j,t}$ would be 0 if there is no link between agents i and j). We define $w_{i,j,t}$ as follows:

$$w_{i,j,t} = \frac{1}{4} \times \frac{\theta_{i,j,t}}{n(N_{i,t})} \quad (18)$$

where $N_{i,t}$ is the set of neighbors of agent i at time t , and $n(N_{i,t})$ denotes the number of elements in this set. The indirect trust score of bank i to bank j could be calculated as follows:

$$\theta_{i,j,t} \approx \sum_{k \in N_{i,t}} w_{i,k,t} \theta_{k,j,t} \quad (19)$$

This means that in order to calculate the level of trust of a counterpart if there is a direct relationship, agents use Equation 17; otherwise, they need the consensus of other agents based on Equation 19 (maybe in a recursive mode).

5.4 EXPERIMENT AND RESULTS

5.4.1 Simulation Experiments

We study the IMM dynamics in a situation where banks are required to enforce Basel III rules for interbank liquidity management consistently. We simulate the IMM within three typical economic cycles and then add a blockchain-based trust mechanism to each cycle and simulate it again. For this paper, we first test three economic growth scenarios, proxied by three levels of uncertainty, in the absence of blockchain (off-chain mode) using the parameters shown in Table 5.2.

Table 5.2. Parameters for different economic cycles. This table lists the parameters expressing the uncertainty in different economic conditions for use in the simulation.

Parameter	Growth	Decline	Recession
	(no uncertainty)	(moderate uncertainty)	(high uncertainty)
$\sigma_c, \sigma_l, \sigma_{al}$	$\mathcal{U}(0,0.005)$	$\mathcal{U}(0.05,0.1)$	$\mathcal{U}(0.1,0.25)$
σ_d, σ_p	$\mathcal{U}(0,0.003)$	$\mathcal{U}(0.03,0.06)$	$\mathcal{U}(0.06,0.15)$

In the next step, we intervene the algorithm for consensus in the blockchain on the level of trust between banks and test the previous three scenarios again in the new environment (on-chain mode). We run each simulation 10 times in order to smooth out irregularities. Finally, we compare the results of these six experiments and discuss the findings.

Each of these setups assumes that banks face an abundance or lack of liquidity with specific dynamics. Banks under setup ‘growth’ face occasional surpluses or shortages of liquidity, as there is no uncertainty. Due to moderate uncertainty, banks in the situation of ‘decline’ are mainly faced with a lack of liquidity, but sometimes there is an abundance. Finally, under a ‘recession’ environment, banks face large dispersions in the lack or excess of liquidity. The values of the other parameters used in our study are the same for all scenarios and are as shown in Table 5.3.

Table 5.3. Regulatory and calculation parameters. This table lists all the parameters used in the simulation.

Parameter	Description	Value
N_B	Number of banks	413
N_C	Initial number of banks’ counterparts	20
IRC	Interest rate corridor	[0,0.02]
λ_s	Coefficients of fire selling securities	[0,0.15]
λ_c	Coefficients of fire selling facilities	[0,0.15]
α	Leverage requirement	0.03
ϵ	Minimum capital adequacy requirement	0.045
π	Counter-cyclical capital buffer	[0,0.025]
ω_c	Risk-weight for commercial loans	1
ω_l	Risk-weight for interbank loans	0.2
$\bar{\rho}$	Minimum liquidity coverage ratio	1
β_1	Regression coefficient for interaction with the central bank (X_1)	1.0174

β_2	Regression coefficient for equity (X_2)	43.5843
β_3	Regression coefficient for competitiveness (X_3)	-7.7397
β_4	Regression coefficient for net interest income (X_4)	-7.4634
β_5	Regression coefficient for size (X_5)	-0.8392
κ_1	Endpoint for the trust level -1	-20.3913
κ_2	Endpoint for the trust levels 0 and 1	-18.8518
κ_3	Endpoint for the trust levels 1 and 2	-17.7525
κ_4	Endpoint for the trust levels 2 and 3	-16.3817
κ_5	Endpoint for the trust levels 3 and 4	-14.9349

We also set the consensus algorithm to tolerate f Byzantine nodes where the total number of nodes is $n \geq 3f + 1$ as a typical adversary mode setting in most algorithms (e.g. Practical Byzantine Fault Tolerance (PBFT) (Castro and Liskov 1999), Redundant Byzantine Fault Tolerance (RBFT) (Aublin et al. 2013), BFT-SMART (Bessani et al. 2014), and HotStuff (Yin et al. 2018)).

5.4.2 Results and Discussion

This section presents the results of 10 simulation runs of each of the six economic cycle–trust setups. Each experiment is based on an independent draw of the initial network for interbank loans as well as the balance sheet amounts of different banks. All initial networks are formed by setting 20 as the initial value of the number of each bank’s counterparts (see Section 5.3.1 for more details). However, as the simulation progresses, it is possible for banks to make new relationships over time. For this purpose, if a bank can not borrow from its existing counterparts, it will apply for a loan from other banks in the network. In off-chain mode scenarios, the acceptance of the request by a new lending bank is $1 - \sigma_i$ likely but at a higher premium than what the other partners of that bank pay. In on-chain mode scenarios, condition $\theta_{i,j,t} + \tau_{i,t} > 4$ must be met to accept the request by a new lending bank (see Section 5.3.4), and the

interest rate will be subject to the same procedure as the other counterparts of the bank (between the ceiling and the floor of the corridor). Results of simulation experiments are in Figures 5.1–5.8.

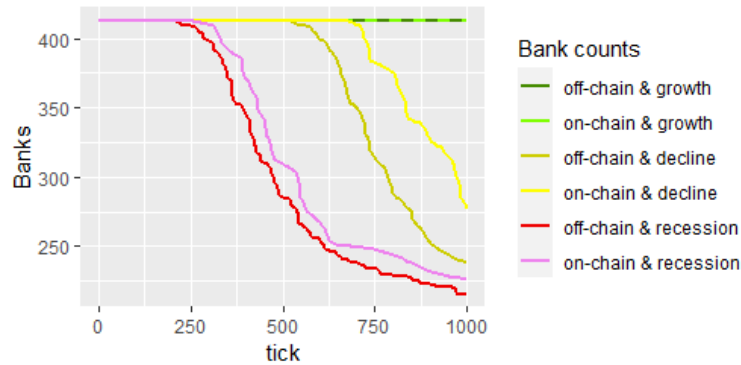


Figure 5.1. Evolution of banks in times of various economic situations: off-chain vs. on-chain modes. The figure shows the stability of banks in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

Comparing the number of banks in both off-chain and on-chain modes during 1000 days of activity in times of economic growth in Figure 5.1 shows the stability of banks throughout the period. This means that when uncertainty is low, banks meet each other's liquidity needs well, and no default or failure is observed. From Figure 5.2, the monthly moving average of the total number of loans in the vast majority of periods in the off-chain mode (69%) is in a position above the 'number of banks' line ($n = 413$). It seems that in this mode, the general tendency of the borrowing banks is to borrow from more partners, and most of the lending banks tend to diversify their interbank loan portfolio and lend to more banks (i.e. extensive margin). Another possible reason for this could be the dual activity of some banks, which act as both lender and borrower in one day. By the intervention of the use of blockchain in the model, this trend goes surprisingly down the line (79%), meaning that both parties prefer to reduce the number of agreements and increase the amount instead (i.e. intensive margin). The slight gap between the two curves of the total amount of interbank loans for these two modes in Figure 5.3 confirms this claim.

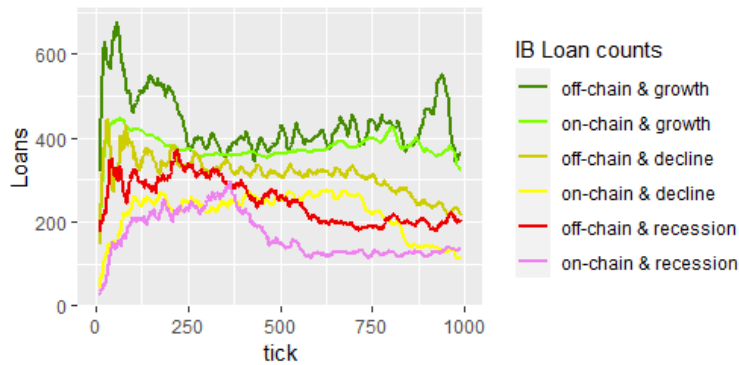


Figure 5.2. Evolution of the number of interbank loans in times of various economic situations: off-chain vs. on-chain modes. The figure shows changes in the number of interbank loans in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

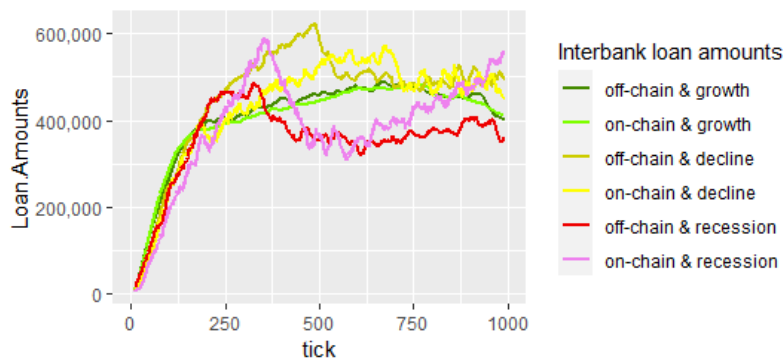


Figure 5.3. Evolution of total amount of interbank loans in times of various economic situations: off-chain vs. on-chain modes. The figure shows changes in the amount of interbank loans in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

Figure 5.1 provides a similar comparison for the economic decline situation. The simulation results of the proposed consensus algorithm to build trust among market members show that although the use of this algorithm and the blockchain cannot ultimately prevent cascades of failure, they can delay it at least for a considerable time. This 157-day deadline is a golden opportunity for the regulator to use its monetary instruments and policies to find a way to maintain stability and restore calm to the market. During a recession, this excellent opportunity is reduced to 47 business days. Similar to economic growth scenarios, there are significant gaps between off-chain and

on-chain modes in both the number and the total amount of loans in times of economic decline. Opposing the direction of gaps (Figure 5.2 vs. Figure 5.3) confirms the previous argument about adopting strategy ‘intensive margin’ instead of strategy ‘extensive margin’ when using blockchain. It is likely that the failure of banks and reducing their number increase the gap between the total loans amount in the off-chain and on-chain modes. The gap between the number of loans in these two modes remains almost constant.

In addition to Figure 5.3, Figures 5.4–5.8 provide a comparison between the aggregate values of each of the balance sheet operations of market members in the two off-chain and on-chain modes at the times of economic growth, decline, and recession. According to Figures 5.4–5.8, except for the economic growth situation, where the gap between total amounts in the case of using the blockchain-based trust mechanism and the case without it is negligible over time, the other balance sheet items have a significant positive difference in the on-chain mode with the off-chain mode.

One noteworthy point is the difference between the refinancing amounts of banks by the central bank. As shown in Figure 5.4, at the time of economic growth, although the trend of central bank lending is upward in both the off-chain and on-chain modes, the total amount of these loans in the on-chain mode is decreasing over time. Less central bank intervention in the market in the circumstance of building trust using blockchain is fully in line with the approach of using this technology for decentralization. In the conditions of economic decline, the process of central bank intervention in the market becomes almost constant before the failure of some banks and then declines. During a recession, this trend is downward from the beginning and after about half of the simulation time is fixed. In both the situations, the amount of loans granted by the central bank in the on-chain mode is higher than in the off-chain mode, meaning that the use of blockchain alone can not stabilize the market, and especially in abnormal economic conditions, there is a greater need for regulatory intervention in the market. Although we do not simulate the central bank’s balance sheet in this study, the increase in banks’ reserves confirms the sufficiency of the

central bank's resources to more intervene in the market in times of crisis (see Figure 5.5).

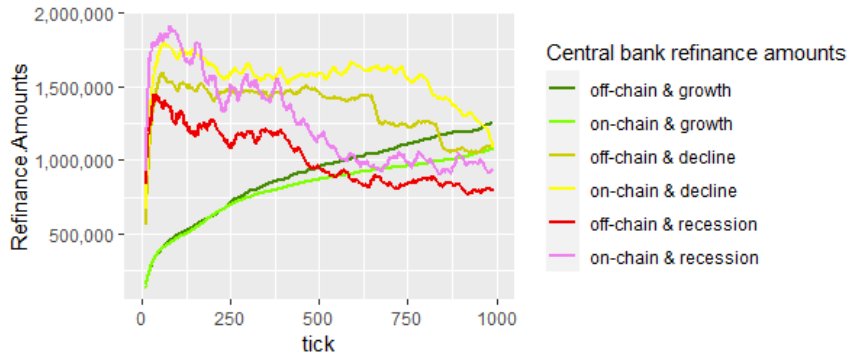


Figure 5.4. Evolution of total amount of the central bank refinances in times of various economic situations: off-chain vs. on-chain modes. The figure shows changes in the amount of the central bank's refinances in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

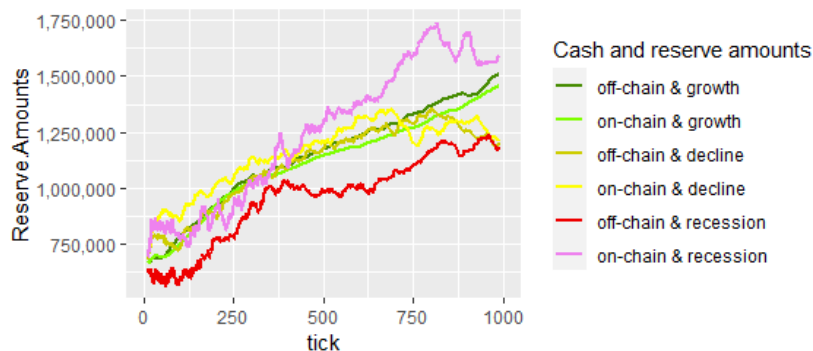


Figure 5.5. Evolution of total amount of reserves in times of various economic situations: off-chain vs. on-chain modes. The figure shows changes in the amount of banks' cash and reserve in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

Figure 5.6 shows that in contrast to the off-chain mode, where the amount of client deposits has decreased with the failure of banks (i.e. intensification of distrust in society affected by distrust in the IMM), in the on-chain mode, even after the delayed failure of indebted banks, not only has clients' trust in the remaining banks in the market not decreased, but the total amount of deposits has also increased. The increase in banks' reserves in the abnormal circumstances (Figure 5.5) confirms this. Another

noteworthy point is that in the on-chain mode, even before the cascading failure of banks, the amount of liquidity provided by clients (i.e. term deposits and demand deposits) is higher than in the off-chain mode. The question that which of the client deposits' or the interbank loans' growth does influence the other's growth can be considered as a topic for future research. However, what is certain is that the increase in the amount of client deposits in lending banks is the most important factor in enabling these banks to provide market liquidity and lend to banks in need in abnormal economic conditions.

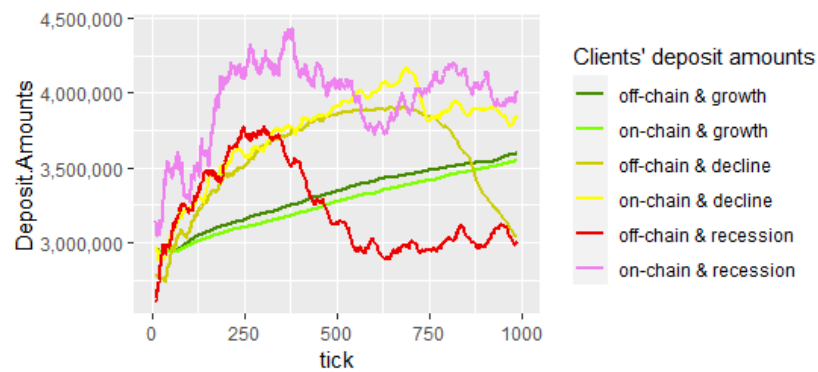


Figure 5.6. Evolution of total amount of clients' deposits in times of various economic situations: off-chain vs. on-chain modes. The figure shows changes in the total amount of banks' client deposits in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

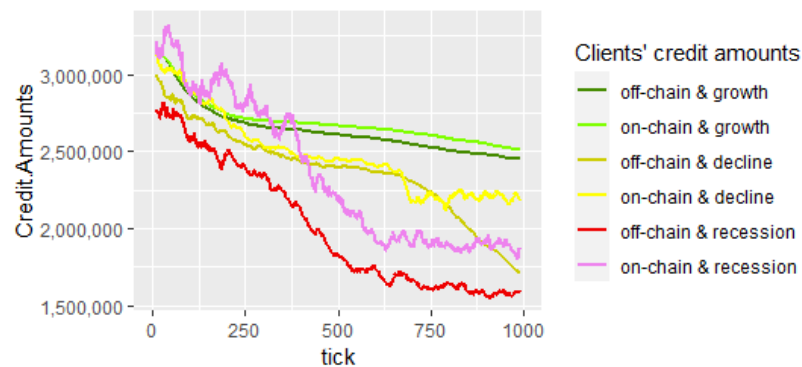


Figure 5.7. Evolution of total amount of clients' credits in times of various economic situations: off-chain vs. on-chain modes. The figure shows changes in the total amount of banks' client loans in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

The simulation results show that in all cases, banks reduce lending to clients in order to perhaps invest more in securities and meet the regulatory requirements. However, as shown in Figure 5.7, in the on-chain mode, banks are able to grant more credit to their clients. In this mode, the behavior of banks in lending to clients, even in situations of economic decline and recession, maintains its correlation with their behavior in times of economic growth, except when cascading failures occur, which, of course, after a while, client credits return to the correlation balance.

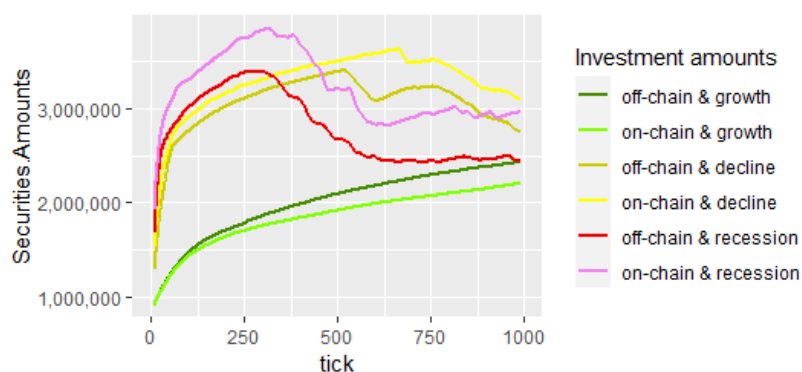


Figure 5.8. Evolution of total amount of investment in securities in times of various economic situations: off-chain vs. on-chain modes. The figure shows changes in the total amount of banks' client loans in different economic conditions throughout the simulation time when banks adopt off-chain or on-chain strategies.

Figure 5.8 shows that in all cases, the interest of banks in investing in securities increases over time. However, it is only in the case of economic growth that this tendency in the mode of using blockchain is less than in the mode of not using this technology. The main reason for this might be that in the context of economic stability, the proposed trust algorithm ensures sufficient profitability of banks from lending in a reliable interbank market so that they feel less need to invest in a parallel market. As stability in the economy decreases, the tendency of banks to invest in other markets in the on-chain mode increases more than in the off-chain mode and correlates with it.

Measurements based on retention of banks in the system show that the use of blockchain-based consensus leads to a similar situation with not using it only in times of long-term economic growth with low uncertainty. However, according to the

findings above, the results of using blockchain for periods of long-term economic decline with moderate uncertainty and long-term recession with high uncertainty are much more promising. Continuous use of blockchain to maintain trust among banks indicates positive effects on the stability of the IMM in different economic cycles, as more banks survive, at least for a while.

Positive effects are seen in times of downturn, even at the highest levels of uncertainty, and it can be inferred that the use of this technology can overcome the distrust caused by the uncertainty transferred to the market by external factors (mainly customers) for a while and provide an opportunity for the regulator to mitigate systemic risk and avoid a banking crisis. In fact, similar to the situation in which banks in the economic growth cycle are able to focus without any worries on both interbank lending and investing in other assets such as securities, as the level of uncertainty increases, the focus of banks on lending interbank funds can continue for a significant period of time based on the trust reached by consensus in the market.

5.5 CONCLUSION AND FUTURE WORKS

This paper presents an agent-based simulation platform for the interbank market and integrates it with the notion of trust using a proposed consensus algorithm to reduce the effects of uncertainty caused by different economic conditions. In this setting, the stochastic mismatch between clients' loan flows and their deposit flows leads to liquidity needs in banks. Banks also try to make a profit by investing in securities. In order to compensate for the lack of liquidity of their peers, banks lend them overnight without collateral, in full compliance with Basel III regulations. In the event that a bank is unable to borrow from other banks, the central bank will refinance it against securities. Under certain circumstances, some banks may have to fire sell in order not to default.

Like most researchers in this field who face the problem of almost non-existent reliable data on interbank exposures (Teply and Klinger 2019), our main limitation in

this study is the lack of access to actual IMM data to calibrate the model and compare simulation results with past realities. However, we combine theory and practice in the model to calibrate it with data created based on the real-world aggregate balance sheet of the French banking system.

Based on the simulation results, the banking network remains stable during periods of economic growth without any additional need for a mechanism to strengthen trust. However, by increasing the uncertainty caused by changes in economic conditions, the establishment of a blockchain-based trust mechanism in the market can help maintain trust between banks and, consequently, market stability. Although such a mechanism is not able to fully protect the market from systemic risk and contagious failures in the long run, it undermines the destructive effects of uncertainty, at least until the central bank overcomes it through appropriate monetary instruments and policies.

Although this paper attempts to add to the literature of trust among banks by experimenting with a blockchain-based recommender system and reporting its successful use, a new issue can be raised: trust in technology, that is, trust in the platform and trust in records (Y. Lu et al. 2010), which we leave to future research. Furthermore, even though banks apply interest rates within a corridor in our model, this corridor system is static. Adding a dynamic corridor system to the platform that also covers negative interest rates, in addition to the ability to pay interest on banks' reserves, could be another subject for future works. The funds exchanged on this platform are now all overnight. Even in the case of central bank refinancing against banks' securities, we have not gone beyond simply pledging the securities in return for the loan. Adding secured lending processes and mechanisms such as repo to the model can make it more helpful in simulating real-world events in the future.

The last point is that in our model, banks' decisions about lending, buying securities, etc., like other events that take place outside their control, have a stochastic basis. Another direction of research in the future can be the use of artificial intelligence by adding learning methods and algorithms to the model so that agents make decisions

based on their current and future goals and using what they learn from the past and considering the behavior of other agents. Maintaining trust between agents can be one of the goals to which they apply what they learn in using blockchain to conduct more trustful transactions in the future.

6 CONCLUSION

CONCLUSION AND IMPLICATIONS FOR POLICY AND FURTHER RESEARCH

6.1 SUMMARY AND CONTRIBUTIONS OF THE STUDY

This dissertation, consisting of four essays, aims to answer a series of questions regarding the effects of using blockchain in the interbank market. The first article laid the foundation for the rest of the dissertation by answering the question of what are the main IMM concerns and the factors affecting them. By employing a set of bibliometric analyses of 609 publications, including journal articles, conference proceedings, book chapters, theses, working papers, etc., in the field of IMM, this essay identified five themes as the main concerns of participants of this market, which affect their decisions regarding liquidity supply and demand. Based on the findings of this stage, it was concluded that systemic risk, stability, network structure, trust, and default are the most critical issues that market participants consider in liquidity supply and demand. The roots of each concern (i.e. the factors influencing the concerns) were then explored through a detailed review of 160 documents published in the last two decades that focus on these five concerns. At the same time, the essay showed how these factors affect the concerns and listed strategies different market players adopt in facing the factors.

The body of knowledge created in this study enables researchers, in addition to finding categories of all opinions for and against the phenomena related to IMM, to situate their research correctly under one or more identified themes. Also, to address the gap in knowledge regarding the lack of a concrete definition of the IMM, this article provided an IMM definition integrating all perceptions of the interbank market, liquidity provision methods, and related procedures in the literature. Moreover, by identifying the gaps in the existing research in this field, the essay suggested nine areas for future studies – stability, default, network, balance sheet, central bank, liquidity, contagion, dynamics, and capital.

Based on the findings of the first article and in response to the questions raised in the second article, that is, what design of a blockchain-based multi-agent architecture with learning agents can support IMM dynamics, a conceptual design of a distributed system for IMM was presented. The proposed system was made by combining a number of learning agents specific to each market member, where different agents are responsible for performing their own functions. Also, a mechanism was proposed to integrate the system with the blockchain so that the agents responsible for registering loan transactions between members record these transactions on the blockchain. Accordingly, if there is a need for consensus in a specific case, e.g. the trustworthiness of a bank, other agents can adopt a mechanism to endorse the trust level of that bank. Furthermore, agents in the system will be able to use their past data along with their beliefs, desires, and intentions to improve their future behaviors.

In order to address the gap related to the lack of an ABM that covers market concerns to help market decision-making, the third and fourth essays focused on the development of the simulation platform. Aiming to fill the research gap on blockchain and ABM integration, the third paper proposed a simple algorithm for trustworthiness consensus, completed in the fourth paper. The algorithm in the third essay was developed on a real blockchain integrated into the IMM simulation platform, while in the fourth essay, it was developed through the abstraction of blockchain connections within a network environment.

Simulations of the system with different amounts of uncertainty, which were considered as proxies for different economic conditions and, as a result, different overall levels of trust, revealed that the higher the uncertainty in the market (i.e. the more unstable the economic situation and the lower the public confidence in the market), the sooner the market collapse will occur. When agents used blockchain to record their loan transactions and reach a consensus on the trust level of loan applicants, the market showed more stability for a reasonable period due to the reduction of information asymmetry among actors, even in the face of economic instability. This means postponing the cascade of failures until after this period.

This research clearly illustrates the increase in market stability due to the increase in trust in the banking network and, as a result, the decrease in the likelihood and number of defaults and the reduction of systemic risk. However, it also raises the question of what policies can be adopted by the regulator in order to intensify this stability and save the market from failure after this period of postponement has passed. Also, while the use of blockchain increases stability in the market, this approach provided new insight into the shift in banks' lending portfolio strategy from the extensive margin (i.e. diversifying loan portfolio and lending to more banks) to the intensive margin (i.e. reducing the number of contracts and increasing in volume instead).

6.2 LIMITATIONS OF THE STUDY

Like any other research, conducting research under the subject of this dissertation has faced limitations in various stages, the most important of which are reported in the essays. This section provides a summary of these limitations. Concerning the literature, although both gray literature and peer-reviewed articles from scientific databases have been reviewed to reduce the likelihood of publication bias, it is possible that limiting the number of databases and central banks as well as focusing only on the publications in English limit the number of included documents and the scope of the survey.

Emphasizing that the title or abstract must contain certain phrases and removing the results containing irrelevant terms can also be considered another limitation.

Regarding the architectural design of the system, the main limitation could be that only a high-level design was presented, and no part of the system was implemented and tested yet. The main focus of the following two essays was on removing this limitation and developing the essential parts of the system so that it validated the proposed architecture by testing a number of scenarios and ensuring the performance of the system. The most critical limitation mentioned in the third essay was the limitation of hardware resources for simultaneous allocation to the virtual nodes of the blockchain network, which leads to the simulation of the system with only 30 random banking agents. In order to overcome this weakness, in the fourth essay, the integration of the simulation platform with blockchain led to developing an abstract blockchain using network concepts.

However, the lack of access to actual IMM data to calibrate the model and compare simulation results with past realities remains the biggest limitation of this research. Another issue that could affect the results and findings of this research is the use of stochastic bases for banks' decisions in cases under their control, e.g. lending, which is, like some other events, out of their control. In this regard, it would be better to use cognitive agents that use a set of basic rules to make decisions (E.R. Smith and Conrey 2007) or learning agents that learn from their past experiences and behave according to a set of factors (Brearcliffe and Crooks 2021). However, the main obstacles to realizing such approaches are lack of access to real data to train agents and limited project time.

6.3 IMPLICATIONS OF THE STUDY

Some benefits of the knowledge derived in this dissertation for academics and practitioners include the following. First, the literature review conducted in this dissertation serves as a guide for future studies of researchers in the field of IMM;

Because it strengthens the academic field by providing a summary of what has been done so far and what needs to be done in the future. Also, since this survey deals with rooting out the main concerns of IMM actors, its findings can help banks and central banks better understand the factors influencing the market to make changes or improve some of their market strategies if necessary. For example, central banks may consider that information is an influential factor in particular concerns, and therefore providing an infrastructure to overcome information asymmetry in the market will help reduce systemic risk and, consequently, increase stability in the market. It can even lead to developing a set of resolutions and instructions to be implemented by all banks. Another example is the characteristics of banks, which, according to the reviewed literature, affect the largest number of concerns. Therefore, maybe the customization of some regulations according to the different characteristics of banks, including size, position in the market, etc., is a way to increase resilience and prevent the collapse of the banking network in times of crisis.

Second, since the presented design of the system relies on the findings of the first essay and also pays attention to other published works regarding the integration of IMM and blockchain, it can be considered a basis for developing an intelligent agent-based system for trading in IMM. It can be used in the future by central banks or third-party companies active in financial market solutions, especially those developing interbank payment and settlement or depository systems. There may also be researchers interested in developing and testing the system for new business processes and financial products using blockchain technology.

Third, the prototype developed using two software platforms, Repast Symphony and Corda, provides a concrete example of the feasibility of integrating interbank market solutions with blockchain. At the same time, the obtained results show a better performance of the system compared to the current centralized systems in terms of stability and resiliency of the market. All that needs to be done is the development of (i) interfaces to connect banks' trading systems to the blockchain and (ii) an interbank loan system including smart contracts and consensus methods required in the blockchain. The consensus model developed in this dissertation for endorsing the

trustworthiness of banks can be a basis for future developments in this regard. Also, one may use the same model of consensus in other areas where trust plays a central role. Supply chain management is one of these fields where maintaining trust between system components is an important concern, and research focused on blockchain has grown in recent years (Qian and Papadonikolaki 2020, Yuan et al. 2020, Batwa and Norrman 2021). Another area consists of renewable/sustainable energy markets, which in many cases seek to use blockchain to create a trustworthiness network between small producers, consumers, etc., as well as issuing reputation tokens (Pipattanasomporn et al. 2018, Aloqaily et al. 2020).

Fourth, the ABM presented for IMM in this research, which is integrated with blockchain, can serve as a null model for researchers to investigate the impact of applying various financial frameworks and monetary policies in a blockchain-enabled interbank market. In particular, this is not only a way to give more time to the central bank in its role of ‘lender of last resort’ (Bagehot 1873, Allen et al. 2009), it can be useful for finding policies that take advantage of the delay in the collapse of the market due to the use of blockchain and by changing regulations, routines, etc. keep the market on its toes until calm returns. Also, by implementing the logic related to CBDC¹⁴ in the blockchain module, the effects of using this new currency in the banking network can be evaluated. Another vital point for banks and the central bank is that since blockchain is an essential factor in ensuring market resilience, the resiliency of its infrastructure should be taken into account in times of stress so that it can meet expectations.

In addition, there are several risks and potential complications associated with the application of blockchain technology in the interbank market, including:

1. Regulatory compliance: One of the main risks associated with blockchain in the interbank market is regulatory compliance. Regulations vary widely

¹⁴ Central Bank Digital Currency

across different countries and regions, and it is important to ensure that any blockchain-based system complies with relevant laws and regulations.

2. **Security risks:** Blockchain technology is not immune to security risks, and there is always a risk of attacks on the system. It is important to implement appropriate security measures to prevent unauthorized access, hacking, and other forms of cybercrime.
3. **Operational risks:** As with any new technology, there are operational risks associated with implementing blockchain in the interbank market. These may include technical glitches, system downtime, and other operational issues that could impact the functioning of the market.
4. **Integration with existing systems:** Many existing systems in the interbank market may not be compatible with blockchain technology, and integrating new systems with legacy systems can be challenging and time-consuming.
5. **Privacy concerns:** While blockchain technology is inherently secure, there are concerns around the privacy of sensitive data. It is important to ensure that the right privacy and security measures are in place to protect sensitive information.
6. **Interoperability:** Different blockchain networks may not be compatible with each other, which could create interoperability issues and limit the usefulness of the technology.
7. **Governance:** Blockchain networks require effective governance structures to ensure that decisions are made in a transparent and accountable manner. Developing effective governance structures can be challenging and requires careful consideration.

6.4 FUTURE AVENUES

Those future directions mentioned in the essays of this dissertation that have not been realized in any of the essays, in addition to some future research related to the dissertation as a whole, are presented in this section. First of all, further research is needed to determine the interbank network's quality as it is the basis of most research models in the field of IMM. Finding ways to evaluate a set of quality characteristics for the network, e.g. security, reliability, availability, predictability, stability, transparency, etc., can ensure the quality of members' activity. In such an environment that can be evaluated at any time by measuring quality indicators, the general equilibrium to be solved by researchers in the future is to maximize the quality of both the entire network (as the goal of the central bank) and sub-networks between banks (as the goal of the participating banks). The latter includes both the quality of the nodes (i.e. default risk, systemic importance, etc.) and the edges (i.e. trust relationships, collaterals, etc.).

Another opportunity for future research is the study of the mechanisms and effects of securely publishing market data. The issue of the release of which information with what level of access and among which actors result in the highest level of transparency, trust, and stability, as well as the lowest amount of default and systemic risks, is an issue that has not been addressed so far. Both categories of research focused on the technical infrastructure of information sharing, such as blockchain, and the regulator's policies regarding matters such as transparency, confidentiality, etc. are included in this direction.

Regarding the evaluation of the level of trust of banks applying for loans, since the positive and negative records of loan relationships can be interpreted as belief and disbelief, and uncertainty is a parameter affecting the behavior of agents, a future study can combine the method presented in the dissertation with the method proposed by Cheng et al. (2021), which basically uses these items in calculating trust. In order to replace the basis of agents' behavior with current stochastic approaches, future studies could address adding learning algorithms to the model so that agents make decisions based on their goals, use what they learn from the past, and consider the behavior of

other agents. Maintaining trust between agents can be one of the goals to which they apply what they learn in using blockchain to conduct more trustworthy transactions in the future.

Furthermore, even though banks apply interest rates within a corridor in our model, this corridor system is static. Adding a dynamic corridor system to the platform that covers negative interest rates, in addition to the ability to pay interest on banks' reserves, could be another subject for future work. Also, the funds exchanged on the platform are now all overnight. Even in the case of the central bank refinancing against banks' securities, the model does not go beyond simply pledging the securities against the loan. Adding secured lending routines such as repo to the model can make it more helpful in simulating real-world events in the future. Moreover, the results in this dissertation do not support the case of a 'Black Swan' event that could cause a systemic collapse. A scenario in which a recession abruptly follows economic growth can be of interest to scholars and practitioners to simulate and analyze the market in off-chain and on-chain modes.

Involving machine learning in simulating the behavior of banks based on past data are other topics that can be considered in future research. One important use case for incorporating learning agents in our model in the future is to make it as realistic as possible. To achieve this, we can use learning models such as LSTM¹⁵, which can predict the future behavior of agents in terms of balance sheet operations based on past data, instead of relying on random number generation functions. However, this approach requires a significant amount of data to train and test the model, which may not be readily available in officially published data. Nevertheless, if such data can be obtained, using learning agents can significantly enhance the accuracy and realism of our model. In addition to their potential contribution to creating banks' balance sheets,

¹⁵ Long short-term memory

learning techniques can also enhance the quality of group decision-making (consensus) among banks when it comes to endorsing borrowers.

Credit rating agencies, which are independent institutions, continuously calculate and announce the credit rating of banks. These ratings are used to evaluate the creditworthiness and systemic risk of banks in the market. In addition, indicators like DebtRank are used to assess the potential impact of a bank's failure on the overall financial system. It could be valuable to design scenarios to compare the effectiveness of using centralized trust mechanisms, such as credit rating certifications or public evaluations, with the trust mechanism proposed by us. Additionally, future research in this field could explore scenarios that combine our proposed mechanism with some of these centralized methods. These studies could provide insights into the strengths and weaknesses of different trust mechanisms and help identify ways to improve the overall efficiency and effectiveness of financial systems.

In our model, the central bank agent is responsible for clearing and settlement in the interbank market. To generate the vector of incoming and outgoing payments of each bank with other banks, we use a Gaussian random process. The central bank then forms the matrix of interbank payments, performs settlement operations, and announces the settlement vector of each bank. However, in our current model, the only risk-reducing and stability-creating role for the central bank is to intervene in the market through refinancing banks against their securities. While this is an important function, there are other roles that a central counterparty (CCP) can play, such as acting as a guarantor intermediary, facilitating netting, and promoting standardization. Therefore, future research could explore the potential benefits of adding these CCP tasks to our model and examining the system with and without blockchain technology. Our research shows the usefulness of using blockchain technology in an environment where settlement is done centrally by a CCP. However, in the future, we plan to test a scenario where the CCP is removed from the settlement process, and settlement is done on the blockchain with the consensus of network members. In this new scenario, we will compare the results with our previous findings to determine if this approach has additional benefits or drawbacks. This comparison will help us better understand

the potential impact of blockchain technology on the interbank market and inform future research on the topic

While the reversal of central bank funding in on-chain and off-chain modes during different market regimes may be influenced by the population of active banks (i.e. more defaults in off-chain mode), certain ratios such as the average central bank refinance (total central bank refinance divided by the number of active banks) could provide a better interpretation of the simulation results. Additionally, we plan to further explore the effects of blockchain technology on the balance sheets of banks in future publications and identify reasons for changes in behavior. It is possible that these effects may vary depending on bank characteristics, such as size, and will require further study. It is always a good idea to consider different factors that could impact the results and outcomes of a study. Including an analysis of bank size, for example, can provide additional insights into how different types of institutions may be affected by the use of blockchain in the interbank market.

Blockchain technology provides a unique opportunity to enable the implementation of smart contracts, which can facilitate the accurate execution of market rules in a distributed environment. The consensus mechanism among market members regarding the conclusion and execution of smart contracts is a key feature of blockchain technology. Our simulation results demonstrate that the use of blockchain for recording interbank loan transactions can effectively build trust among market members. However, since the decision-making structure in blockchain can vary depending on the consensus method used, more simulations are needed to determine the optimal governance structure for a blockchain-based IMM environment. As with cryptocurrencies, future research can explore comparing consensus methods to enhance both security and efficiency in the context of IMM and increase trust and efficiency. As explained in Chapter 5, we have implemented the Byzantine Fault Tolerant (BFT) consensus mechanism in our model. However, we acknowledge the potential benefits of other consensus mechanisms such as Practical Byzantine Fault Tolerant (pBFT) and Byzantine Fault Tolerant Raft (BFT Raft). Therefore, we plan to

explore and evaluate the effectiveness of these consensus mechanisms in our model in the future.

7 RÉSUMÉ EN FRANÇAIS

À travers la présentation de quatre articles, cette thèse s'intéresse à un marché financier spécifique ayant un grand impact sur l'économie, à savoir le marché monétaire interbancaire (MMI). La principale différence entre ce modèle et les modèles traditionnels du MMI est que les acteurs du marché effectuent des transactions de prêt entre eux sur une plateforme blockchain, une technologie qui semble pouvoir favoriser la confiance entre les acteurs lorsque cela est nécessaire et ainsi augmenter la stabilité du marché. Ce modèle à base d'agents (MBA), incluant les banques et la banque centrale, utilise une approche stochastique ainsi qu'un processus de calibration pour rendre le comportement des agents aussi proche de la réalité que possible dans les simulations du MMI. Ce résumé donne un aperçu de ce domaine et de la littérature pertinente, et après avoir souligné l'importance du sujet, il explique la conception de la recherche et la relation entre les chapitres (articles ou essais). Les résultats de chaque article et leur apport à la littérature sont présentés comme les limites inhérentes à ce travail de recherche. Ce résumé se conclut sur les futures voies de recherche possibles.

7.1 DÉFINITION DES CONCEPTS CLÉS

7.1.1 Marché Monétaire Interbancaire

Le MMI est un marché officiel national ou international où les banques se prêtent mutuellement de grosses sommes d'argent lorsqu'elles ont besoin de liquidités,

principalement sur une courte période. Les déficits des banques sont notamment dus aux retraits stochastiques des déposants, qui créent des chocs de liquidité intermittents (Bruche et Suarez 2010). Par exemple, lorsqu'un grand nombre de déposants retirent son argent d'une banque, celle-ci peut se retrouver à court de liquidités et être obligée de compenser en empruntant à d'autres banques. Autrement dit, une banque dont les crédits accordés augmentent davantage que les autres banque voit ses dépôts augmenter plus rapidement que les autres et en conséquence aussi ses dettes interbancaires réglées en monnaie banque centrale (MBC), cette MBC devant être empruntée sur le MMI. Ce prêt peut être non garanti (basé sur la confiance) ou garanti (basé sur des garanties d'actifs). Dans le cas de prêts garantis, la banque centrale peut également intervenir sur le marché en achetant ou en vendant des obligations d'État pour accroître ou réduire la liquidité du système bancaire (opérations d'open market - OOM). En revanche, les prêts non garantis sont généralement accordés pour de brèves périodes (par ex., un jour), principalement sur la base de la relation de confiance entre le prêteur et l'emprunteur et de leurs antécédents de prêts (Affinito 2012, Iori et al. 2015, Temizsoy et al. 2015, Kobayashi et Takaguchi 2018).

7.1.2 Blockchain

La blockchain est un grand livre « distribué » (partagé) et immuable qui facilite le processus d'enregistrement des transactions et de suivi des actifs, qu'ils soient tangibles (par ex., l'argent) ou intangibles (par ex., la propriété intellectuelle), dans un réseau d'affaires. Aujourd'hui, cette technologie est passée d'une technologie de pointe à une technologie qui change de paradigme (Patel et al. 2020). Il existe au moins quatre grands types de réseaux blockchain : public, privé, hybride et consortium. Une blockchain publique (par ex., Bitcoin et Ethereum) est absolument non restrictive et sans permission, où toute personne ayant accès à l'Internet, en devenant un nœud autorisé, peut publier une transaction ou participer à la vérification d'une transaction. En revanche, un réseau de blockchain qui fonctionne sur un réseau fermé (par ex., à l'intérieur d'une organisation) ou qui est contrôlé par une seule entité est une blockchain privée. La blockchain hybride combine des éléments des blockchains

privées et publiques, permettant aux organisations de contrôler qui peut accéder à des données spécifiques stockées dans la blockchain, et quelles données seront ouvertes publiquement. La blockchain de consortium est une blockchain privée dans laquelle plusieurs membres organisationnels collaborent sur un réseau décentralisé. Elle élimine les risques de contrôle du réseau par une seule entité. Il est intéressant de noter que dans une blockchain de consortium, les procédures de consensus sont contrôlées par des nœuds prédéfinis. Nous utilisons ce type de blockchain dans la modélisation retenue d'un marché interbancaire fondé sur une blockchain.

7.1.3 Modélisation basée sur les agents

La MBA implique la représentation informatique d'un ensemble de micro-entités (agents) qui interagissent et évoluent dans le temps, et leurs interactions forment un macro-système (Epstein et Axtell 1996, Grimm et Railsback 2012). Adaptée de la notion de systèmes multi-agents, la MBA se compose généralement de trois éléments (Macal et North 2014). Le premier élément est un ensemble d'agents qui composent le système adaptatif complexe. Chaque agent est caractérisé par des caractères spécifiques (par ex., la taille, le rôle sur le marché) et des comportements (par ex., prêter, emprunter, faire défaut). Un agent qui peut avoir différentes natures (par ex., prêteur, emprunteur) peut être autonome, volontaire, intelligent (capable de s'adapter et d'apprendre), hétérogène, dynamique et en interaction, et ses états internes peuvent varier dans le temps. Le deuxième élément est un ensemble de relations et de méthodes d'interaction des agents (également appelé règles de décision ou modèle conceptuel) qui décrit comment les agents interagissent entre eux et avec leur environnement, et comment leurs états internes évoluent. L'environnement des agents (par ex., le marché interbancaire) est le troisième élément qui peut parfois ne pas être pris en compte dans la construction d'un MBA s'il n'est pas pertinent pour le processus étudié. Cependant, si l'environnement est pris en compte, il peut être passif ou actif avec des caractéristiques dynamiques et des règles de comportement.

La MBA est particulièrement utile et attrayante lorsque le système modélisé est complexe et adaptatif ; qu'il implique des agents autonomes, hétérogènes et intelligents ; que l'environnement est crucial et non fixe ; et que les interactions dynamiques entre les agents ou entre les agents et l'environnement se forment et se dissipent par intermittence, ce qui ajoute à la complexité (Bonabeau 2002, Siebers et al. 2010). En bref, la MBA est une approche ascendante qui permet de découvrir les comportements et les mécanismes causaux au niveau individuel menant à des phénomènes émergents agrégés au niveau macro (McAlpine et al. 2020). Pour ce faire, une population, un environnement et des modèles doivent être reproduits de manière à ce que le modèle produise des caractéristiques ou des résultats similaires à ceux observés dans le monde réel (Wilensky et Rand 2015). Afin d'étudier le marché monétaire interbancaire et d'étudier les effets de l'utilisation de la blockchain dans ce marché sur la confiance et d'autres enjeux concernant ce marché, la modélisation basée sur les agents est utilisée comme outil principal dans cette recherche pour les raisons suivantes :

- Le comportement de chaque banque du système est non linéaire et peut être caractérisé par des seuils et des règles conditionnelles (Nier et al. 2007, T. Xu et al. 2016a, Li et al. 2019). Il est impossible ou difficile de décrire la discontinuité du comportement individuel par les méthodes traditionnelles (Bonabeau 2002), par exemple, la modélisation mathématique.
- Le comportement non-markovien et les corrélations temporelles dues à la mémoire, à la dépendance au comportement des autres banques et à l'hystérésis conduisent les banques à s'adapter (Barroso et al. 2016, Liu et al. 2018).
- Les interactions des banques sont hétérogènes et peuvent générer des effets de réseau connus sous le nom de risque systémique (Nier et al. 2007, Halaj 2018). Les méthodes traditionnelles supposent généralement un mélange homogène global, mais l'interaction des banques dans un réseau

et la topologie de ce réseau peuvent entraîner des écarts importants par rapport au comportement global prédit (Bonabeau 2002).

- Les méthodes qui utilisent des moyennes ou qui tendent à lisser les fluctuations sont inefficaces pour cette étude, car le système bancaire peut être linéairement stable mais instable aux chocs et perturbations importants (T. Xu et al. 2016a, Halaj 2018, Gaffeo et al. 2019).

7.2 CONTEXTE DE L'ÉTUDE

Un MMI, étant soumis à un environnement économique hautement stochastique (Mitja Steinbacher et Jagrič 2020), est un système adaptatif complexe (Glass et al. 2011, Chiriță et al. 2022) où les banques se prêtent de grandes quantités d'argent aux taux interbancaires lorsqu'elles ont besoin de liquidités pour une courte période, s'adaptant ainsi à cet environnement stochastique. Le MMI joue un rôle crucial dans le système bancaire, et plus largement, dans le système économique en refinançant les banques en liquidité, conduisant au financement de l'économie par le secteur bancaire (Freixas et Jorge 2008a, Mistrulli 2011, Craig et al. 2015). Un MMI qui se bloque rend impossible ou trop coûteux le refinancement des banques intrinsèquement lié à leur activité d'octroi de crédits (Allen et al. 2014, Bucher et al. 2019). Dans un tel cas, le financement à moyen et long terme des autres entreprises peut immédiatement se tarir. Cette situation se transforme rapidement en une récession majeure et en une hausse du taux de chômage (De Haas et Van Horen 2012, Acharya et Merrouche 2013). Par exemple, la crise des subprimes de 2007 et la faillite de Lehman Brothers en septembre 2008 ont entraîné des dysfonctionnements tangibles sur le marché et une forte détérioration de l'activité économique.

Les besoins en liquidités des banques évoluent en permanence, ce qui fait qu'une banque prêteuse de liquidités aujourd'hui, peut devenir l'emprunteuse dès le lendemain. La gestion de la volatilité des taux d'intérêt due à la dynamique de l'offre et de la demande quotidienne de liquidités est principalement dévolue aux banques

centrales (Freixas et Rochet 2008). L'importance de cette question tient au fait que l'instabilité du marché peut entraîner un risque plus élevé de faillites bancaires et de contagion (Brock et Suarez 2000, Barroso et al. 2016), voire des crises bancaires et l'apparition de profonds ralentissements (Gurgone et al. 2018, Popoyan et al. 2020). Les chocs de marché causés par le déclin de l'économie affectent les relations de prêt et modifient ainsi la structure du marché. En bref, l'augmentation de la demande de liquidités sur le marché fait grimper les taux d'intérêt (Taylor et Williams 2009), ce qui, parallèlement à l'augmentation des retraits des clients, affaiblira la situation des banques débitrices. Il est probable que certaines banques disposant de liquidités excédentaires refusent de prêter par crainte de l'insolvabilité de leurs homologues et de la perte de leur capital (Aldasoro et al. 2017, Serri et al. 2017). D'autres prêteurs peuvent ne pas tenir compte des relations de prêt antérieures et demander des primes plus élevées pour des contrats identiques ou demander des titres très liquides en garantie (Barroso et al. 2016), en particulier pour les emprunteurs plus risqués.

Ces difficultés à compenser les déficits de liquidité peuvent conduire au défaut de certaines banques débitrices et finalement à leur faillite (Taylor et Williams 2009, Barroso et al. 2016). La faillite des banques, d'une part, détruit la confiance du public envers le système bancaire, augmente les retraits et diminue la liquidité sur le marché, et d'autre part, provoque plus de défiance chez les banques prêteuses, ce qui conduit à la thésaurisation de la liquidité par celles-ci et à l'apparition d'une crise de liquidité sur le marché (Heider et al. 2009, Acharya et Merrouche 2013, Gale et Yorulmazer 2013). Tous ces éléments conduisent à intensifier la crise économique. La crise financière de 2007–2008 est un bon exemple pour illustrer les interrelations entre la liquidité et la capacité des institutions financières à rembourser les dettes et pour prouver le rôle important du MMI dans l'économie (Adrian 2015). Bien que les prêteurs relationnels aient joué un rôle clé en tant que fournisseurs de liquidités, ils ont néanmoins obligé les emprunteurs à payer des primes élevées pour les transactions (Liberati et al. 2015, Temizsoy et al. 2015).

Les résultats de la revue de la littérature dans ce domaine montrent que la *contagion* et le *risque systémique*, la *stabilité*, la *structure du marché*, la *relation* et la *confiance*, ainsi que le

défaut et la défaillance sont les critères les plus critiques qui affectent les décisions des acteurs du marché dans l'offre et la demande de liquidité au sein du MMI. La banque centrale cherche à réduire le risque systémique et à prévenir la contagion financière (Li et al. 2015, Barroso et al. 2016, Leventides et al. 2019), ainsi qu'à gérer le réseau (Acemoglu et al. 2015, León et al. 2018) de manière à rendre le MMI plus stable et plus résistant aux chocs (Acemoglu et al. 2015, Hübsch et Walther 2017, Leventides et al. 2019). En outre, les banques tentent de maintenir leurs relations de prêt (Fricke et Lux 2015, Kobayashi et Takaguchi 2018). et de réduire le risque de manquement aux obligations légales (Li et al. 2015, Barroso et al. 2016).

L'un des principaux défis mentionnés par de nombreux chercheurs dans ce domaine est la surconfidentialité des informations du marché, en particulier des informations relatives aux transactions de prêt, et le manque d'accès facile à ces informations. Il est donc impossible pour les acteurs du marché d'accéder aux informations de leurs pairs et d'estimer leur degré de fiabilité. Plusieurs chercheurs se sont penchés sur l'effet positif de la disponibilité de l'information pour réduire le risque systémique (Thurner et Poledna 2013, Barroso et al. 2016, Ding et al. 2017) et accroître la confiance (Affinito 2012, Anand et al. 2012, Marzo et Zagaglia 2014, Craig et al. 2015). Étant donné que l'avènement de la technologie blockchain, qui est considérée comme la plateforme dominante pour le développement dans l'avenir de la monnaie numérique de la banque centrale (MNBC), pourrait fournir des facilités pour l'enregistrement et le partage sécurisés des informations de marché (Lewis et al. 2017, Paech 2017), la simulation d'un MMI bénéficiant de cette technologie est étudiée dans cette thèse.

L'idée principale concernant l'utilisation de la blockchain sur le marché interbancaire est qu'elle devrait d'abord garder les informations d'exposition entre les banques confidentielles pour les deux extrémités de la relation. Ensuite, elle devrait être en mesure de fournir les informations nécessaires aux banques pour évaluer le risque de leur contrepartie et les aider à prendre des décisions concernant les prêts aux banques emprunteuses en fournissant ces informations aux nœuds qui en ont besoin dans le réseau. Le consensus est une procédure par laquelle les pairs d'un réseau

blockchain parviennent à un accord sur l'état actuel des données dans le réseau. Il semble qu'un consensus entre un certain nombre de banques sur le niveau de confiance à avoir envers une banque donnée puisse aider les banques prêteuses dans leurs décisions de prêter à cette banque.

Pour observer les effets de ces facteurs externes (par ex., l'adoption de la technologie blockchain) sur les sujets d'enjeu concernant le MMI (par ex., la contagion ou la stabilité) qui manquent de preuves empiriques solides, les chercheurs ont souvent recours à des méthodes de simulation pour tester comment un ensemble d'expositions dans différentes conditions affectera les banques individuellement ainsi que l'ensemble du réseau bancaire (Upper 2011). Les résultats de l'enquête sur les méthodes et approches utilisées en recherche dans le domaine du MMI montrent que la MBA pour la simulation est l'une des trois méthodes les plus utilisées (voir Figure 2.7). Grâce à la MBA, le réseau des expositions interbancaires et les événements de défaut peuvent être générés de manière endogène à partir des règles comportementales suivies par les agents bancaires. Il s'agit là de l'avantage le plus important de cette approche par rapport aux méthodes telles que les tests de résistance, qui ne fournissent généralement pas plus que quelques instantanés du système bancaire, même lorsque des informations détaillées sur les expositions bilatérales des banques sont disponibles (Iori et al. 2015).

7.3 IMPORTANCE DE L'ÉTUDE

Dans un vaste réseau de marchés financiers, où chaque nœud représente plusieurs opérations de marché, de nombreuses entités interagissent de manière non linéaire les unes avec les autres, ce qui en fait un système complexe. Sans aucun doute, le MMI est l'un des systèmes les plus complexes en matière de politique bancaire et monétaire (Gai et al. 2011, X. Gao et al. 2017, Roukny et al. 2013). La multiplicité des acteurs dont les rôles changent constamment de prêteur à emprunteur et vice-versa, surtout lorsque la banque centrale intervient sur le marché en tant que prêteur en dernier ressort, ainsi que la variété des méthodes de prêt, sont les principales raisons de cette complexité. Le caractère stochastique de la demande globale de liquidités à court terme et la

probabilité de défaillances en chaîne de concurrents étroitement liés dans cet environnement sont une autre source de complexité. Un autre aspect de la complexité est la différence des enjeux des participants au marché et leurs effets différents sur les objectifs et les décisions des banques et de la banque centrale concernant l'offre et la demande de liquidités. À tout cela s'ajoute l'asymétrie de l'information que subissent les différents acteurs en raison de la difficulté d'accès à l'information et cela est d'autant plus prégnant pour les petits acteurs.

Une façon de réduire la complexité d'un système avec ces spécifications pourrait être d'utiliser une MBA auto-organisée (Haber 2010). La MBA fournit une représentation informatique d'un ensemble de micro-entités (d'agents) qui interagissent entre elles et évoluent dans le temps pour former un macro-système (Epstein et Axtell 1996, Grimm et Railsback 2012). En tant qu'approche ascendante, la MBA permet de découvrir les comportements individuels et les mécanismes de causalité qui conduisent à des phénomènes de niveau macro (McAlpine et al. 2020). Cependant, avant de concevoir et de construire un modèle à base d'agents du MMI, il est nécessaire d'identifier avec précision l'environnement du MMI, le comportement des agents et les facteurs affectant la prise de décision et l'interaction des agents entre eux et avec leur environnement proche. Il convient de mentionner que, bien que les règles et les procédures des marchés interbancaires de différents pays soient proches lorsqu'on regarde globalement, elles diffèrent, le plus souvent, lorsqu'on rentre dans les détails et elles dépendent des politiques des banques centrales. Par conséquent, l'absence d'un cadre commun unique est l'un des problèmes de la recherche dans ce domaine.

En ce qui concerne la résolution du problème de l'asymétrie d'information, l'utilisation de la technologie blockchain est considérée comme une solution potentielle (Yu et al. 2018). En raison de la complexité du MMI et du nombre de participants impliqués et des interactions entre eux, la technologie blockchain peut aider à réduire l'asymétrie d'information en garantissant que tous les participants au marché disposent de toutes les informations nécessaires pour prendre la décision de prêter ou non aux nœuds demandeurs. L'un des défis que cette thèse cherche à relever est de trouver un

moyen pour les banques de parvenir à un consensus dans la blockchain sur le niveau de fiabilité d'une banque emprunteuse candidate.

Premièrement, à notre connaissance, aucune définition concrète unique du MMI ne peut être trouvée dans la littérature, car les recherches pertinentes sont principalement basées sur les données disponibles dans des pays particuliers, et chaque pays a généralement son propre marché interbancaire, ce qui entraîne des variations dans la structure et la définition. De nombreux chercheurs considèrent un certain nombre de facteurs influents comme des critères de décision dans le MMI (par ex., Furfine (2003), Martínez-Jaramillo et al. (2010), Angelini et al. (2011), Acharya et Merrouche (2013), Dičpinigaitienė et Novickytė (2018)) et plusieurs chercheurs étudient divers aspects de ce marché (par ex., Hasman (2013), Dičpinigaitienė et Novickytė (2018), Pozlep (2018)). Cependant, nous pensons qu'il manque encore une étude complète qui identifie les racines des principaux enjeux concernant le MMI et les intègre dans le corpus de connaissances de ce domaine. Ainsi, la réalisation d'une revue systématique de la littérature comme première étape de la rédaction de cette dissertation,

- vise à fournir une définition globale et complète du MMI qui n'a pas déjà été fournie par les chercheurs dans ce domaine.
- résume les preuves disponibles sur les enjeux spécifiques des acteurs et les critères qu'ils utilisent largement dans la sélection des stratégies de marché.
- identifie les lacunes dans la recherche existante afin de suggérer des domaines pour des études futures.
- fournit un contexte permettant de positionner de nouvelles activités de recherche.

Deuxièmement, ces dernières années, de nombreuses recherches partielles ont été menées à l'aide de la simulation à base d'agents sur le risque systémique (par ex., Barroso et al. (2016), Gurgone et al. (2018), Halaj (2018), Calimani et al. (2019)), sur la

stabilité (par ex., Gurgone et al. (2018), Popoyan et al. (2020)), sur la structure du marché (par ex., Georg (2013), Gurgone et al. (2018)), sur la confiance (par ex., Iori et al. (2015)) et enfin sur le défaut (par ex., Barroso et al. (2016), Smaga et al. (2018)) au niveau du MMI. Cependant, il est rare de trouver un travail rigoureux et global utilisant un modèle à base d'agents qui couvre l'ensemble de ces critères pour aider à la prise de décision sur le marché. La deuxième étape de cette recherche, la conception d'un système à base d'agents, contribue à la littérature de trois façons :

- en fournissant une architecture basée sur des agents qui prend en charge toutes les fonctions et critères associées à l'offre et à la demande de liquidités dans le MMI.
- en établissant un mécanisme de haut niveau pour l'utilisation d'agents d'apprentissage dans la conception de systèmes.
- en envisageant l'utilisation de la blockchain dans le cadre de l'architecture du système cible.

Troisièmement, à notre connaissance, il existe peu d'études sur l'application de la blockchain dans le MMI. Guo et Liang (2016) mentionnent quelques normalisations par certaines associations et pays concernant l'utilisation de la blockchain dans le MMI. Cucari et al. (2021) discutent d'une étude de cas du projet Spunta dans le secteur bancaire italien et montrent comment le projet utilise la blockchain pour créer une plus grande transparence et visibilité, une exécution plus rapide et la possibilité de transférer des chèques et de l'argent directement dans le réseau bancaire. De plus, les études dans le domaine des systèmes à base d'agents qui impliquent d'une manière ou d'une autre la blockchain dans leur conception et qui se concentrent sur des enjeux communs avec celles du MMI telles que la confiance sont très peu nombreuses. On peut compter parmi cette catégorie Calvaresi et al. (2018b), qui mettent en œuvre un système pour calculer la réputation des agents à l'aide de contrats intelligents et permettent de suivre l'évolution de leur réputation, et Khalid et al. (2021), qui proposent de maintenir la

confiance dans un marché énergétique distribué basé sur des agents en publiant des informations sur les accords entre agents dans la blockchain, mais rien sur le MMI.

Il semble y avoir une lacune en ce qui concerne l'utilisation de la blockchain dans le MMI, compte tenu du rôle que cette technologie jouera dans l'avenir du secteur bancaire (Patel et al. 2020). Une MBA qui peut aider à étudier les effets de l'utilisation de la blockchain dans le MMI apportera une contribution significative pour combler cette lacune. Les deux dernières étapes (Chapitres 4 et 5) de cette recherche doctorale contribuent à la littérature d'au moins deux façons :

- en enrichissant la littérature sur la confiance interbancaire.
- en utilisant la blockchain (une fois une blockchain réelle et une autre fois une blockchain abstraite) comme partie intégrante de la plateforme de simulation.

7.4 QUESTIONS DE RECHERCHE

Cette recherche vise à trouver des réponses aux questions suivantes qui peuvent être classées dans trois catégories :

- Quelles sont les principaux facteurs influençant les décisions des acteurs du MMI ? Quelles sont les origines de chacun de ces facteurs ? Quels sont les mécanismes qui lient ces origines aux différents facteurs ?
- Quelle conception de l'approche multi-agents peut intégrer toutes les dynamiques du MMI ? Comment cette conception peut-elle bénéficier de la blockchain pour accroître la stabilité du marché ? Comment les agents peuvent-ils stocker leurs connaissances et apprendre pour atteindre un meilleur consensus sur les transactions du marché ?

- Quel est l'effet de différents niveaux d'incertitude, en tant que proxy de la confiance, sur la stabilité du système bancaire dans différentes situations économiques ? L'utilisation de la blockchain peut-elle contribuer à accroître la confiance entre les banques et à stabiliser le marché en période de crise ?

7.5 APPROCHE ET MÉTHODE DE RECHERCHE

À notre connaissance, le lien entre le MMI et la blockchain n'a pas été abordé auparavant. Par conséquent, une approche exploratoire utilisant la modélisation basée sur les agents (Kuhlmann 2021) a été adoptée pour mener cette recherche en raison des avantages mentionnés à la section 7.1.3. De nombreuses simulations utilisant la MBA peuvent être trouvées dans la littérature sur le marché interbancaire (voir Sections 2 à 5). Il convient de noter que les recherches utilisant cette modélisation, combinée à l'utilisation de la blockchain, sont émergentes dans d'autres domaines tels que la chaîne logistique mais inexistantes concernant le MMI. Étant donné que l'intégration de la blockchain au MMI est un nouveau sujet, l'objectif de cette recherche exploratoire est de découvrir les relations possibles entre les variables, et donc, aucune hypothèse préalable n'est prévue.

La Figure 7.1 illustre les processus qui relient le système bancaire aux données pertinentes, au développement du modèle et au résultat final. Comme pour toute étude, l'argumentation peut être faite en collectant des données à partir de diverses sources d'information (la Banque de France, la Banque centrale européenne et la Réserve fédérale). Les paramètres du modèle sont développés à travers un processus d'abstraction. Les abstractions sont comparées aux données empiriques pour évaluer leur validité dans un processus appelé calibrage. Le calibrage fournit la base pour des résultats fiables du modèle. Enfin, les résultats de la simulation du modèle sont testés dans le cadre d'un processus appelé validation.

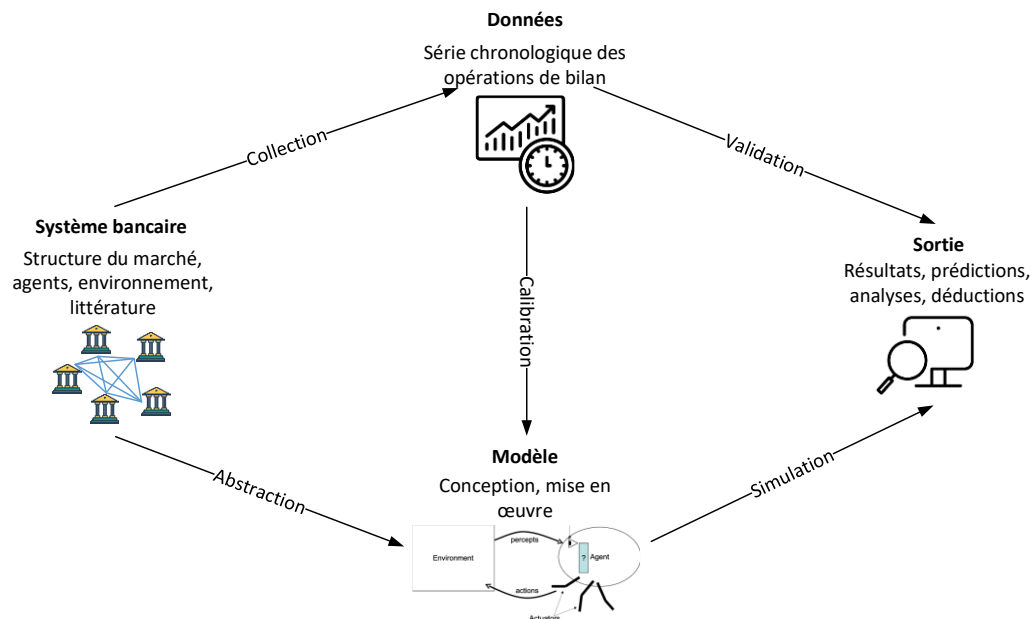


Figure 7.1. Approche de recherche sur l'influence de la blockchain sur le MMI. La figure présente le processus de réalisation de l'étude, du concept aux résultats, en montrant la relation entre le système bancaire, la conception du modèle, les sources de données et les résultats du modèle. Les actions clés du processus de recherche sont indiquées par des flèches directionnelles.

Dans le cadre de cette approche, un processus en quatre étapes basé sur la méthode Design Sprint (Banfield et al. 2015, Keijzer-Broers et Reuver 2016) constitue la méthodologie globale de recherche. Design Sprint est une méthodologie éprouvée fondée sur un processus itératif, qui permet de résoudre des problèmes par la conception, le prototypage et le test d'idées. L'approche itérative permet au chercheur de créer et de tester rapidement des idées et d'itérer rapidement sur les idées prometteuses jusqu'à ce qu'elles soient suffisamment formées pour être développées. Les quatre principales étapes de la méthodologie adoptée, que les quatre essais de cette thèse décrivent, sont brièvement présentées ci-dessous. En plus de façonner la méthodologie globale du projet, cette approche itérative a été utilisée pour mener à bien chaque étape du projet et réaliser les produits finals de cette étape. Les détails de chaque étape sont fournis dans les Sections 2 à 5.

1. Carte : Cette étape consiste à cartographier le problème et à choisir les domaines importants sur lesquels se concentrer. Elle commence par la réalisation d'un certain nombre d'analyses bibliométriques sur 609

publications dans le domaine du MMI afin d'identifier les critères de décision des acteurs du marché. Ensuite, en examinant en détail 160 publications axées sur ces critères, on identifie les facteurs qui les affectent et la stratégie des banques face à chaque facteur. Tout ceci est réalisé pour comprendre les différentes questions dans le domaine du problème, en examinant, synthétisant et comparant les études existantes pertinentes.

2. Esquisser et décider : Cette étape esquisse des solutions concurrentes sur des diagrammes pour prendre des décisions et transforme les idées en hypothèses testables. Cela se manifeste dans la conception d'un système multi-agents pour le marché interbancaire qui utilise la blockchain pour enregistrer les transactions de prêt entre les banques, et qui suggère également des mécanismes permettant aux banques d'atteindre un consensus sur la blockchain et d'apprendre des comportements passés. Un ensemble de diagrammes UML sont utilisés pour la conception dans cette étape.
3. Prototype : Cette étape consiste à construire un prototype réaliste du système sur la base de la conception et des décisions prises à l'étape précédente. L'objectif est de créer un prototype de « qualité Boucle d'Or ». Idéalement, la qualité doit être suffisamment bonne pour paraître aussi réelle que possible, mais pas au point de prendre beaucoup de temps à construire. Le prototype du MMI intègre rapidement une plateforme de la MBA avec une blockchain réelle, construit rapidement un modèle d'agents interagissant ensemble, met en œuvre un algorithme de consensus minimal sur la blockchain, et mène des expériences avec un petit nombre d'agents pour explorer leurs relations de prêt.
4. Test : En utilisant le feedback reçu du test du prototype, cette étape complète le modèle dans le but de respecter au maximum les exigences fonctionnelles et apporte les changements nécessaires à l'architecture et au code de la plateforme de simulation pour se conformer aux exigences non

fonctionnelles. Les exigences fonctionnelles à respecter dans cette étape comprennent l'achèvement des règles du marché et la méthode de consensus. Les exigences non fonctionnelles sont principalement axées sur les performances de la plate-forme en surmontant les difficultés liées à la limitation des ressources matérielles et à la parallélisation des processus. Enfin, les scénarios précédents sont testés à nouveau sur la nouvelle version de la plate-forme et les résultats sont analysés.

7.6 ORGANISATION DE LA THÈSE, PRINCIPAUX RESULTATS ET LIMITES

Le corps principal de cette recherche se compose de quatre essais. Dans la dénomination des essais, outre la mention du titre de l'article, un titre abrégé basé sur les étapes de la méthode Design Sprint est également utilisé. Ce nom attribue la nature de chaque essai et les efforts déployés pour celui-ci à une phase de Design Sprint qui a toujours été prise en compte lors de la mise en œuvre de chaque étape de cette recherche.

7.6.1 Carte : Une Analyse Documentaire

Le premier essai pose la question de savoir quelles sont les principaux critères de décision des acteurs du marché monétaire interbancaire et les facteurs qui influencent ces critères, et comment l'ensemble de ces facteurs façonne les stratégies des acteurs. Aujourd'hui, après plusieurs crises bancaires au cours de ces dernières décennies, il existe une littérature considérable sur les facteurs influençant les décisions d'offre et de demande de liquidités par les banques et la banque centrale sur le marché interbancaire. Cependant, en ce qui concerne certains facteurs, aucun consensus n'a été atteint parmi les chercheurs pour savoir si ces effets sont positifs ou négatifs sur des critères tels que la stabilité et la structure du marché. Nous soutenons que cette absence d'accord est due à l'absence d'un cadre théorique solide dans ce domaine qui

aborde en détail toutes les problèmes de fonctionnement du MMI et les facteurs qui les affectent. En effectuant une analyse scientométrique et une revue systématique de la littérature récente, cet essai redéfinit le MMI et fournit un modèle des critères influençant les décisions des acteurs du MMI.

Étant donné que les recherches connexes expriment principalement le point de vue établi dans certains pays sur la notion de MMI en fonction des données accessibles dans ces pays et que chaque pays a généralement son propre MMI, on observe des structures et des définitions différentes. Par conséquent, cet essai commence par fournir une définition unifiée des MMI. Nous définissons le MMI comme

« un marché officiel national ou international où les banques se prêtent mutuellement d'importantes sommes d'argent lorsqu'elles ont besoin de liquidités, principalement sur une courte période ».

Cette définition fait référence de manière exhaustive à tous les aspects recherchés du marché interbancaire. Elle fait référence (i) à la formalité du marché et au fait qu'il est contrôlé par une entité de régulation ; (ii) à sa distribution géographique, qu'elle soit nationale ou internationale ; (iii) à la principale chose négociable sur le marché, c'est-à-dire la liquidité ; (iv) aux principaux processus du marché, c'est-à-dire le prêt et l'emprunt ; et (v) à la nature à court terme du marché. Cette définition nous fournit un critère pour décider d'inclure ou d'exclure les documents recherchés dans le processus d'examen à un stade ultérieur.

Après avoir énoncé le problème et l'importance de mener une recherche, cet essai utilise une approche itérative dans la mise en œuvre d'une méthodologie d'examen systématique basé sur SALSAS¹⁶ (Grant et Booth 2009). Tout d'abord, en effectuant une analyse bibliométrique des mots-clés et une exploration de texte dans le titre et le résumé de 609 publications, cinq concepts sont identifiés comme les principaux critères de décision des acteurs du MMI. Ces critères sont « la contagion et le risque

¹⁶ Search, Appraisal, Synthesis and Analysis

« systémique », « la stabilité », « la structure du marché », « la relation et la confiance » et « le défaut et la défaillance ». La contagion et le risque systémique font référence à l'interdépendance des banques, et à la transmission des risques à travers l'ensemble du marché. La stabilité correspond à l'état dans lequel le MMI est résistant aux chocs économiques et est apte à remplir sans heurts ses opérations de base pour répondre aux inquiétudes concernant la volatilité des prix et des taux sur le marché. La structure du marché comprend tous les sujets liés à la topologie du réseau et à la configuration du marché, tandis que les relations et la confiance sont liées à l'historique de toutes les relations fiduciaires entre les acteurs du marché. Enfin, le défaut et la défaillance désignent le non-respect des obligations légales d'un prêt.

L'examen détaillé de 160 études portant sur les cinq critères susmentionnés a permis d'élaborer un cadre de recherche dans ce domaine, contenant les facteurs qui influencent ces critères et la manière de les influencer. Outre les caractéristiques du réseau bancaire (la structure du marché), qui comprend un large éventail de facteurs, les caractéristiques des banques, notamment leur taille, sont les facteurs les plus influents sur les critères de décision des banques sur le marché. Le respect des exigences réglementaires en matière de capital et de liquidité, ainsi que les taux d'intérêt et les chocs du marché, sont les facteurs suivants qui, selon la littérature, ont des effets significatifs sur les cinq critères influençant les décisions des acteurs du marché.

Les résultats de l'exploration de texte, sur les recherches futures suggérés dans les publications examinées, aident à identifier les tendances et les orientations de la recherche future sur les enjeux du MMI. Par conséquent, en énumérant un ensemble de thèmes couramment utilisés à cet égard et en présentant une image de l'évolution historique de ces thèmes, cet essai présente un certain nombre de propositions comme pistes futures pour les chercheurs dans ce domaine. Les neuf principaux thèmes qui ont suscité l'intérêt des chercheurs dans la littérature depuis 2013 sont la stabilité, le défaut, la structure du réseau, le bilan, la banque centrale, la liquidité, la contagion, la dynamique et le capital. L'essai se termine par une liste de limites et d'implications, ainsi que par un certain nombre de nouveaux agendas pour l'avenir liés aux résultats de cette recherche. Les plus importants, qui sont liés au sujet de cette thèse, sont l'étude

des mécanismes pour le partage symétrique de l'information entre les membres du marché d'une manière qui aide à améliorer leurs décisions et à augmenter la confiance dans le marché ainsi que l'utilisation de l'intelligence artificielle dans les modèles développés pour prédire les comportements des membres du marché.

7.6.2 Esquisser et Décider : Une Conception Architecturale

Visant à s'atteler aux enjeux identifiés concernant le MMI dans le premier essai, le second essai cherche à découvrir les réponses aux deux questions suivantes : (i) Quelle conception de l'approche multi-agents peut appréhender toutes les dynamiques du MMI, et comment cette conception peut bénéficier de la blockchain pour augmenter la stabilité du marché ? (ii) Dans une telle architecture, comment les agents peuvent-ils stocker leurs connaissances et apprendre pour atteindre un meilleur consensus sur les transactions du marché ? Comme il n'y a pas de réponse claire à ces questions dans la littérature sur le marché interbancaire, cet essai tente de proposer une nouvelle conception architecturale à cette fin en s'appuyant sur la littérature dans les domaines des systèmes multi-agents et de la blockchain et en tenant compte des exigences spécifiques liées au MMI.

Cet essai présente la conception d'une architecture multi-agents pour le marché interbancaire où les transactions de prêts interbancaires sont stockées sur la blockchain afin de réduire l'asymétrie d'information et d'accroître la stabilité du marché, en particulier en temps de crise. Cette architecture est capable de simplifier l'enchevêtrement complexe des différentes routines du marché causé par la multiplicité des acteurs et des différents types de prêts en remplaçant les rôles et les systèmes par un certain nombre d'agents holoniques.

En fait, l'architecture proposée se compose de trois zones principales : la banque emprunteuse, la banque prêteuse et la banque centrale. En général, un agent dans chaque zone est considéré comme responsable de la collecte des données à partir des

systèmes internes ou externes de la banque. Un autre agent est responsable de la planification de la réception ou du paiement des prêts. La responsabilité de négocier avec les agents d'autres banques sur la base d'apprentissages antérieurs et de conclure un accord de prêt incombe également à un autre agent dans chaque zone.

Dans l'architecture proposée, la caractéristique la plus importante de la blockchain est le consensus entre les membres du réseau. Deux types de consensus sont considérés dans cette conception. Le premier est le consensus entre les deux parties à la transaction concernant le montant et les conditions du prêt (le consensus de validité). Ce consensus est créé en présence du nœud de régulation. L'autre est le consensus d'un nombre suffisant de nœuds du réseau concernant l'unicité de la transaction. Dans cet article, nous soutenons que le consensus de validité peut être atteint sur la base des scores que les endosseurs obtiennent en participant au processus d'évaluation des autres nœuds.

Il est supposé que les agents négociateurs des banques qui ne sont pas engagés dans une transaction peuvent agir comme endosseurs de la validité de cette transaction. Voici un exemple permettant aux agents apprenants de créer un meilleur consensus sur la validation des transactions. Supposons que les endosseurs ont des niveaux différents. Les relations de confiance seront particulièrement utiles pour obtenir des recommandations de la part des endosseurs de niveau supérieur. L'un des objectifs de l'intelligence des agents dans le système proposé est de leur permettre d'identifier intelligemment leurs alternatives actuelles, de planifier leurs actions et de répondre aux résultats afin d'instaurer la confiance en trouvant des endosseurs appropriés. Selon l'architecture BDI (convictions-souhait-intentions), une partie des convictions de chaque agent peut inclure une copie de la blockchain contenant les données des transactions auxquelles l'agent a accès. Ces convictions peuvent être justes ou fausses et évoluer dans le temps en fonction du fonctionnement du marché. De même, accepter ou refuser l'aval d'autres agents peut être considéré comme un souhait qui est mis à jour à mesure que les convictions changent. Une fois qu'un ensemble d'actions possibles sont identifiées, l'agent calcule et analyse la récompense, le coût, la priorité,

etc. pour préparer un plan d'action. Le résultat des actions est évalué, et les intentions de l'agent sont mises à jour en conséquence.

Après avoir présenté deux diagrammes de séquence pour deux exemples de scénarios dans le MMI, l'essai se termine par une liste de limites et de travaux futurs. La plus grande limite de cette recherche est qu'elle reste au niveau de la conception et qu'elle n'a pas encore été mise en œuvre et testée avec des données réelles au moment de la publication de l'article. Par conséquent, les travaux futurs pourraient inclure la construction d'un prototype du système. La simulation de ce système avec une plateforme à base d'agents est une autre voie de recherche que nous empruntons dans les essais suivants.

7.6.3 Prototype : Un Modèle Minimal

Après avoir identifié les critères influençant la prise de décision des acteurs du marché interbancaire (le premier essai) et conçu une architecture de haut niveau pour un système à base d'agents intégré à la blockchain pour soutenir les critères mentionnés (le deuxième essai), le troisième essai tente de mettre en œuvre et de tester un prototype d'une partie importante de cette architecture. La principale question d'intérêt dans cette partie de la recherche est de savoir comment et dans quelle mesure l'utilisation de la blockchain peut contribuer à accroître la confiance entre les banques et la stabilité du marché en temps de crise, c'est-à-dire lorsque la confiance diminue.

Pour répondre à cette question, un algorithme de consensus blockchain est conçu pour augmenter la confiance sur le marché par l'endossement des banques qui demandent des prêts. Cette étude combine les deux valeurs du seuil de confiance ($\tau_{i,t}$) de la banque prêteuse et le niveau de confiance réel ($\theta_{i,j,t}$) dans la banque emprunteuse qui est vérifié par les nœuds du réseau blockchain pour la décision des banques en matière de prêt. Le seuil de confiance de chaque banque est calculé en fonction de son interaction avec la banque centrale, de ses fonds propres et de sa taille. Le niveau de confiance réel entre deux banques à tout moment est calculé sur la base de la relation

précédente entre elles, si deux banques ont déjà une relation de prêt ; sinon, il est calculé sur la base de l'endossement d'autres banques avec lesquelles elles ont déjà eu une relation de prêt. Une relation de prêt entre le prêteur i et l'emprunteur j est autorisée à l'instant t si $\theta_{i,j,t} + \tau_{i,t} > 4$. C'est la seule règle sur laquelle les banques fondent leurs décisions de prêt dans ce modèle.

Aussi, la MBA est utilisée comme méthode pour étudier le comportement des différentes banques face à cette technologie proposée. La plateforme de simulation développée pour cette recherche implique une application de prêt simple développée sur la blockchain Corda, qui est intégrée à Repast Symphony pour le développement du modèle à base d'agents du MMI et les simulations. Tous les codes sont développés en langage Java à la fois dans Corda et Repast. Dans ce modèle, différents niveaux d'incertitude causés par différentes situations économiques sont considérés comme des proxys de confiance.

Le simulateur basé sur les agents communique avec le système de prêt par le biais d'une API (interface de programmation d'application) développée dans le cadre du projet. L'étape d'initiation du modèle déploie un nœud de blockchain (Corda) pour chaque agent. Les nœuds de blockchain déployés contenant l'API REST qui enregistre les transactions de prêt sur la blockchain sont ensuite exécutés à ce stade. Par conséquent, l'environnement mis en œuvre pour simuler le comportement des agents est aussi similaire que possible à l'environnement réel que les banques peuvent utiliser dans un MMI réel en employant une blockchain réelle pour enregistrer leurs transactions de prêt.

Bien entendu, cette forme de mise en œuvre (aussi proche que possible de l'environnement réel) comporte des limites. La principale est la puissance de calcul du matériel, qui limite le marché interbancaire simulé dans cette recherche à un réseau de 30 banques. Cette simulation est faite avec 30 agents bancaires qui sont choisis aléatoirement parmi les 413 banques actives sur le marché interbancaire français. Ces agents bancaires sont de petite, moyenne et grande taille et en conformité avec la concentration du MMI français. Ces banques communiquent entre elles en partageant

une partie de leur bilan (les prêts et les dettes interbancaires). Dans ce modèle, tous les prêts interbancaires sont considérés comme non garantis, au jour le jour. De plus, dans ce modèle, l'agent de la banque centrale (la Banque de France), en plus de centraliser la compensation des paiements et d'apparier les liquidités sur le marché, régule le marché et aide les banques à éviter les défaillances lorsque cela est nécessaire.

Cet essai présente d'abord les résultats de la simulation de trois scénarios pour différents cycles économiques en l'absence de blockchain (mode off-chain) et teste ensuite les mêmes scénarios dans le mode où l'algorithme de consensus blockchain proposé est utilisé pour avaliser le niveau de confiance entre les banques (mode on-chain). Les résultats moyens de 10 simulations de chaque scénario pour 350 jours d'activité des banques dans le MMI révèlent la même stabilité des banques dans les modes off-chain et on-chain en cas de croissance économique. Cependant, avec la diminution de la croissance économique et l'entrée dans la crise, l'utilisation d'un tel mécanisme peut retarder la cascade de faillites bancaires pendant une période significative. En outre, les résultats montrent que lorsque la blockchain est utilisée dans une situation économique instable, les banques prêteuses et emprunteuses préfèrent réduire le nombre de contrats et augmenter le montant à la place (c'est-à-dire les relations de confiance).

Le manque d'accès aux données réelles sur l'exposition interbancaire est une autre limite de cette recherche, qui peut être partiellement surmontée par l'interpolation et la désagrégation des données trimestrielles agrégées des bilans des banques et leur conversion en données quotidiennes dans des recherches ultérieures, même si elles ne seront pas considérées comme les données réelles des banques. Le développement d'un modèle qui peut couvrir plus de banques dans la simulation et qui est aussi proche que possible des conditions d'un réseau bancaire réel est un autre élément qui devrait être pris en compte dans les recherches futures. L'utilisation d'un système de corridor de taux d'intérêt, l'ajout de prêts garantis et l'implication de l'intelligence artificielle dans la simulation du comportement des banques sur la base de données antérieures sont d'autres sujets qui peuvent être envisagés dans des recherches futures.

7.6.4 Test : Un modèle maximal

Dans le but d'étendre et de généraliser le modèle présenté dans le troisième essai et ses résultats, ainsi que de surmonter certaines limites mentionnées concernant ce modèle, en particulier le nombre d'agents participant aux expériences, le quatrième essai tente de répondre à deux questions : (i) Quel effet les différents niveaux d'incertitude, en tant qu'indicateur de confiance, ont-ils sur la stabilité du système bancaire dans différentes situations économiques ? (ii) L'utilisation de la blockchain pour accroître la confiance du marché peut-elle augmenter la stabilité en période de baisse de confiance ?

Après avoir passé en revue la littérature décrivant le rôle de la confiance dans le MMI et les documents sur la confiance distribuée utilisant la blockchain, cette recherche cherche à améliorer la logique du modèle. Aussi, l'équation simple pour calculer le niveau de confiance est enrichie en impliquant deux nouvelles variables de compétitivité et de revenu d'intérêt ainsi qu'en utilisant une régression logistique ordinale. En outre, un système de corridor de taux d'intérêt statique est utilisé, dont les limites inférieures et supérieures peuvent être définies comme des paramètres d'expérience.

Pour intégrer un plus grand nombre d'agents dans la simulation, la blockchain Corda laisse place à une abstraction d'un réseau entre banques implémenté par JGraphT. Afin d'établir la règle de décision basée sur le consensus mentionnée dans le troisième article, dans le quatrième essai, toutes les fonctionnalités liées à l'endossement du niveau de confiance des banques emprunteuses sont développées et simulées en utilisant les interfaces de la bibliothèque JGraphT.

L'article étudie la dynamique du MMI dans une situation où les banques sont tenues d'appliquer les règles de Bâle III pour la gestion des liquidités interbancaires de manière cohérente. À l'instar de ce qui a été fait dans le troisième essai, l'article simule ici le marché au sein de trois cycles économiques typiques, puis ajoute un mécanisme de confiance basé sur la blockchain à chaque cycle et simule à nouveau le MMI. Les

valeurs aléatoires de bruit et de dérive qui sont créées en utilisant des distributions uniformes dans différentes conditions économiques sont appliquées dans la production de données de bilan quotidien des banques. D'autres paramètres de simulation sont extraits du cadre de Bâle III et de la littérature sur le marché interbancaire.

Les résultats moyens obtenus à partir de 10 tests de chaque scénario avec 413 agents bancaires confirment plus fortement les résultats rapportés dans le troisième article. On peut déduire du délai plus long des défaillances dans les nouvelles expériences par rapport à ce qui a été rapporté dans le troisième essai que plus il y a de nœuds dans le réseau et, par conséquent, plus les nœuds ont de connexions avec leurs homologues, plus le réseau est résilient. Les résultats confirment les conclusions précédentes selon lesquelles, en mode hors chaîne, la tendance générale des banques emprunteuses est d'emprunter à un plus grand nombre de partenaires, et la plupart des banques prêteuses ont tendance à diversifier leur portefeuille de prêts interbancaires et à prêter à un plus grand nombre de banques (marge extensive). Par l'intervention de l'utilisation de la blockchain dans le modèle, les deux parties préfèrent réduire le nombre d'accords et augmenter le montant à la place (marge intensive), ce qui peut être considéré comme un signe de relations plus empreintes de confiance.

La plus grande limite de cette recherche, comme précédemment, est le manque d'accès aux données réelles détaillées des interactions bancaires, ce qui rend impossible la calibration du modèle. Par conséquent, dans cette recherche, cette calibration n'est rien d'autre que la vérification du modèle avec des données agrégées trimestrielles. En ce qui concerne les pistes futures, l'ajout à la plateforme d'un système de corridor dynamique couvrant également les taux d'intérêt négatifs, en plus de la possibilité de rémunérer les réserves des banques, pourrait être envisagé. Les fonds échangés sur cette plateforme sont actuellement tous au jour le jour. En outre, l'ajout de prêts garantis et de pensions au modèle peut le rendre plus utile pour simuler des événements réels à l'avenir. De plus, dans ce modèle, les décisions des banques en matière de prêts, d'investissements en titres, etc., ont une base stochastique comme d'autres événements qui se déroulent en dehors de leur contrôle. Une autre direction de recherche pour

L'avenir peut être l'utilisation de l'intelligence artificielle et le développement d'agents d'apprentissage qui prennent des décisions en fonction de leurs objectifs actuels et futurs et en utilisant ce qu'ils apprennent du passé.

7.7 VOIES DE RECHERCHE FUTURES

Des recherches supplémentaires sont nécessaires pour déterminer la qualité du réseau interbancaire, car il constitue la base de la plupart des modèles de recherche dans le domaine du MMI. Trouver des moyens d'évaluer un ensemble de caractéristiques de qualité pour le réseau, par exemple, la sécurité, la fiabilité, la disponibilité, la prévisibilité, la stabilité, la transparence, etc. peut garantir la qualité de l'activité des membres. Dans un tel environnement qui peut être évalué à tout moment par la mesure d'indicateurs de qualité, l'équilibre que les chercheurs devront résoudre à l'avenir consiste à maximiser la qualité à la fois du réseau entier (comme objectif de la banque centrale) et des sous-réseaux entre banques (comme objectif des banques participantes). Ce dernier comprend à la fois la qualité des nœuds (risque de défaut, importance systémique, etc.) et des bords (relations de confiance, garanties, etc.).

Une autre possibilité de recherche future est l'étude des mécanismes et des effets de la publication sécurisée des données du marché. La question est de savoir quelles informations publier, avec quel niveau d'accès et parmi quels acteurs, afin d'entraîner le plus haut niveau de transparence, de confiance et de stabilité ainsi que le plus faible montant de risques de défaut et de risque systémique. Cette question qui n'a pas été en effet abordée jusqu'à présent. Les deux catégories de recherche axées sur l'infrastructure technique du partage de l'information, comme la blockchain, et les politiques du régulateur concernant des questions telles que la transparence, la confidentialité, etc. vont dans ce sens.

En ce qui concerne l'évaluation du niveau de confiance des banques qui demandent des prêts, puisque les enregistrements positifs et négatifs des relations de prêt peuvent être interprétés comme de la croyance et de l'incrédulité, et que

l'incertitude est un paramètre qui affecte le comportement des agents, une étude future peut combiner la méthode présentée dans la thèse avec la méthode proposée par Cheng et al. (2021), qui utilise essentiellement ces éléments pour calculer la confiance. Pour remplacer la base du comportement des agents modélisé par les approches stochastiques actuelles, les études futures pourraient aborder l'ajout d'algorithmes d'apprentissage au modèle. Dans ce cas, les agents prennent des décisions en fonction de leurs objectifs, utilisent ce qu'ils apprennent du passé et tiennent compte du comportement des autres agents. Le maintien de la confiance entre les agents peut être l'un des objectifs auxquels ils appliquent ce qu'ils apprennent en utilisant la blockchain pour effectuer des transactions plus fiables à l'avenir.

En outre, même si les banques appliquent des taux d'intérêt dans un corridor dans notre modèle, ce système de corridor est statique. L'ajout d'un système de corridor dynamique à la plateforme qui couvre les taux d'intérêt négatifs, en plus de la possibilité de payer des intérêts sur les réserves des banques, pourrait être un autre sujet de travaux futurs. Par ailleurs, les fonds échangés sur la plateforme sont désormais tous au jour le jour. Même dans le cas du refinancement de la banque centrale contre les titres des banques, le modèle ne va pas au-delà du simple nantissement des titres contre le prêt. L'ajout de routines de prêts garantis, telles que les pensions, au modèle peut le rendre plus utile pour simuler les événements du monde réel à l'avenir. De plus, étant donné la nature des scénarios, les résultats de cette thèse ne confortent pas l'hypothèse d'un événement de type « cygne noir » qui pourrait être à l'origine d'un effondrement systémique. Un scénario dans lequel la croissance économique est brusquement suivie d'une récession peut être intéressant à étudier pour les chercheurs et les praticiens afin de simuler et d'analyser le marché en modes *off-chain* et *on-chain*.

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APPENDICES

APPENDIX A: DETAILS OF BIBLIOMETRIC ANALYSES

As previously mentioned in Section 2.3.1, for building a co-occurrence map based on keywords, we employed the ‘fractional-counting’ method, in which the weight of a co-occurrence link is fractionalized based on the number of other keywords in the publication, rather than ‘full-counting’ method, in which the same weight is calculated for each link. It means that, for example, a publication containing five keywords in the full-counting method is assigned to each keyword with a full weight of 1, and in the case of the fractional-counting method, it is assigned to each keyword with a fractional weight of $\frac{1}{5}$. The fractional-counting method was selected here because, in many situations, including for the purpose of our analysis, it offers a more useful perspective than full-counting (Perianes-Rodriguez et al. 2016). In our case that the number of keywords in the publications remains unchanged over time, misunderstandings or misinterpretations in results obtained through full-counting could have been avoided by fractional-counting.

Adapted from Perianes-Rodriguez et al. (2016), we used K to denote the number of keywords and P as the number of publications included in the analysis. We also used $\mathbf{R} = [r_{kp}]$ to denote a $K \times P$ relatedness matrix where the element r_{ik} equaled 1 if keyword k was in publication p and 0 otherwise. We further used k_p to denote the number of keywords of publication p , that was

$$k_p = \sum_{k=1}^K r_{kp} \geq 1 \quad (1)$$

We used $\mathbf{C} = [c_{kk'}]$ to denote the symmetrical $K \times K$ co-occurrence matrix where the element $c_{kk'}$ equaled the number of fractional-counting coupling links between keywords k and k' and was given by

$$c_{kk'} = \sum_{p=1}^P \frac{r_{kp} r_{k'p}}{k_p - 1} \quad (2)$$

It means that the co-occurrence matrix \mathbf{C} was given by

$$\mathbf{C} = \mathbf{R} \mathit{diag}(\mathbf{R}^T \mathbf{1} - \mathbf{1})^{-1} \mathbf{R}^T \quad (3)$$

where $\mathit{diag}(\mathbf{v})$ denoted a diagonal matrix with the elements of the vector \mathbf{v} on the main diagonal and where $\mathbf{1}$ denoted a column vector of length K with all elements equal to 1. The main diagonal elements of the keyword co-occurrence matrix \mathbf{C} were set to 0.

For making the co-occurrence network, in all iterations, we assessed the ‘association strength’ of the related items to show the similarity between them. van Eck and Waltman (2009) defined it as proportional to the ratio between the observed number of co-occurrences of two objects. It is also the expected number of those objects’ co-occurrences under the assumption that their occurrences are statistically independent. Adapted from van Eck and Waltman (2014), we calculated the normalized association strength values of s_{ij} to normalize for differences between every two nodes i and j in the number of edges they had to other nodes, as in formula 4, where w_{ij} denotes the weight of the edge between nodes i and j (if there is no edge between the two nodes, then $w_{ij} = 0$).

$$s_{ij} = \frac{w_{ij} \sum_i \sum_j w_{ij}}{\sum_i w_{ij} \sum_j w_{ij}} \quad (4)$$

According to van Eck and Waltman (2014), to determine the optimized clusters, each time, we had to maximize the function $C(c_1, \dots, c_n)$, as in formula 5, where c_i denoted the cluster to which node i was assigned, $\delta(c_i, c_j)$ denoted a function that returned 1 or 0 (see Equation 6), and γ denoted a resolution parameter that determined the level of detail of the clustering. In this study, we set γ once to 1.00 and again to 1.20. The higher the value of γ , the larger the number of clusters that will be obtained.

$$\hat{C}(c_1, \dots, c_n) = \sum_{i < j} \delta(c_i, c_j)(s_{ij} - \gamma) \tag{5}$$

$$\delta(c_i, c_j) = \begin{cases} 1, & c_i = c_j \\ 0, & c_i \neq c_j \end{cases} \tag{6}$$

Table A.1 shows the results of the calculations applied to determine the keyword clusters. From Table A.1, it shows that the four clusters identified at this point are inherently well-matched to Zachman’s questions. Semantically, the γ value of 1.20 showed better results for the two questions ‘how’ and ‘when,’ while not changing the two questions ‘why’ and ‘what.’

Table A.1. Result of clustering most common keywords in the field of IMM (1982–2020).

The table shows the characteristics of a network of frequent keywords and their clustering through the bibliometric analysis of documents.

Keyword	Number of links	Total link strength	Occurrences	Avg. pub. year	Cluster	
					$\gamma = 1.00$	$\gamma = 1.20$
Monetary policy	18	104	156	2013	Principles	Principles
Exposure & risk	19	106	149	2014	Principles	Principles
Mortgages	17	76	79	2013	Principles	Principles
Capital	18	40	43	2015	Principles	Principles
Market strategy	17	29	31	2015	Principles	Principles

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Shock & crisis	19	91	108	2014	Operations	Events
Liquidity	19	76	86	2013	Operations	Events
Money supply & demand	19	66	77	2013	Operations	Operations
Interest rate	19	59	71	2011	Operations	Operations
Investment	19	50	52	2012	Operations	Operations
Cross-border channel	19	38	48	2013	Operations	Events
System automation	19	37	39	2014	Operations	Operations
Competition	15	25	31	2010	Operations	Operations
Default & failure	17	37	45	2015	Events	Events
Acts & regulation	14	27	40	2015	Events	Events
Contagion & systemic risk	18	94	183	2016	Concerns	Concerns
Market structure	19	97	138	2015	Concerns	Concerns
Relationship & trust	19	40	56	2015	Concerns	Concerns
Stability	19	39	47	2014	Concerns	Concerns
Complexity	13	27	30	2014	Concerns	Concerns

In the next step, for co-occurrence analysis of the text data (i.e. title and abstract), we employed the ‘full-counting’ method, in which all occurrences of a term in a document are counted, rather than the ‘binary-counting’ method, in which only the presence or absence of a term in a document is important. Like in the previous step, we used T and P to denote, respectively, the number of terms and the number of publications included in the analysis, as well as $\mathbf{U} = [u_{tp}]$ to denote a $T \times P$ usage matrix where the element u_{tp} equaled the number of uses of the term t in the

publication p . We also used t_p to denote the number of term usages of publication p , that was

$$t_p = \sum_{t=1}^T u_{tp} \geq 1 \quad (7)$$

In a similar way with the keyword analysis, we used $\mathbf{C} = [c_{tt'}]$ to denote the full-counting term co-occurrence $K \times K$ matrix where the element $c_{tt'}$ equaled the number of full counting co-occurrence links between terms t and t' and is given by

$$c_{tt'} = \sum_{p=1}^P u_{tp} u_{t'p} \quad (8)$$

The co-occurrence matrix \mathbf{C} was given by

$$\mathbf{C} = \mathbf{U}\mathbf{U}^T \quad (9)$$

Hence, the co-occurrence matrix \mathbf{C} was obtained by post-multiplying the usage matrix \mathbf{U} by its transpose. Self-links in a co-occurrence network were of no interest, and therefore the main diagonal elements of the co-occurrence matrix \mathbf{C} were set to 0.

To calculate the normalized association strength values and determine the optimized clusters, we used formulas 4–6 with the same parameters. As in the previous step, we examined the co-occurrence of terms used in the title and the abstract of the documents with two values, 1.00 and 1.20, for γ . When we set the γ to 1.00, three very large clusters were formed, and the result was not satisfactory. Considering the γ of 1.20, six clusters well mapped to Zachman's framework were formed. Table A.2 shows the clusters that were determined through the analysis of terms within titles and abstracts of the publications.

Table A.2. Result of clustering most frequent terms in the field of IMM (1982–2020). The table shows the characteristics of a network of frequent terms in the title and abstract of documents and their clustering through the bibliometric analysis.

Term	Map to keywords	Number of links	Total link strength	Occurrences	Avg. pub. year	Cluster	
						$\gamma = 1.00$	$\gamma = 1.20$
Asset		51	1,224	128	2014	Cluster1	Principles1
Loan		50	920	106	2012	Cluster2	Principles1
Fund		48	680	76	2009	Cluster2	Principles1
Behavior	Market strategy	50	649	75	2010	Cluster2	Principles1
Monetary policy	Monetary policy	44	654	68	2011	Cluster2	Principles1
Deposit		50	607	60	2013	Cluster2	Principles1
Risk	Exposure & risk	51	2,164	265	2013	Cluster1	Principles2
Policy	Monetary policy	50	949	110	2014	Cluster2	Principles2
Lender	Market strategy	50	873	92	2013	Cluster3	Principles2
Borrower	Market strategy	48	747	70	2013	Cluster3	Principles2
Interbank lending		40	248	31	2012	Cluster1	Principles2
Interbank loan		46	295	34	2014	Cluster1	Principles2
Interest rate	Interest rate	45	1,379	200	2011	Cluster2	Operations1
Cost		48	1,013	111	2012	Cluster2	Operations1
Lending	Money supply & demand	49	887	102	2014	Cluster3	Operations1
Spread	Interest rate	48	678	75	2012	Cluster2	Operations1
Price		47	643	57	2013	Cluster2	Operations1
Demand	Money supply & demand	46	501	50	2010	Cluster2	Operations1
Auction	Competition	37	396	49	2009	Cluster2	Operations1

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Supply	Money supply & demand	46	503	47	2013	Cluster2	Operations1
Bid	Competition	39	492	46	2008	Cluster2	Operations1
Collateral		40	303	44	2012	Cluster2	Operations1
Information		50	996	122	2012	Cluster1	Operations2
Credit		48	556	63	2014	Cluster3	Operations2
Intervention	Intervention	40	339	47	2011	Cluster2	Operations2
Order	Competition	47	333	41	2013	Cluster1	Operations2
Liquidity	Liquidity	51	2,382	294	2012	Cluster2	Events
Crisis	Shock & crisis	51	1,804	217	2013	Cluster3	Events
Shock	Shock & crisis	51	1,813	207	2015	Cluster3	Events
Financial crisis	Shock & crisis	51	1,152	147	2014	Cluster3	Events
Reserve	Acts & regulation	47	830	107	2011	Cluster2	Events
Liquidity shock	Liquidity	48	554	61	2012	Cluster2	Events
International finance	Cross-border channel	44	487	54	2010	Cluster3	Events
Foreign finance	Cross-border channel	40	552	53	2014	Cluster3	Events
Contagion	Contagion & systemic risk	50	1,732	242	2013	Cluster1	Concerns
Systemic risk	Contagion & systemic risk	49	1,531	207	2015	Cluster1	Concerns
Structure	Market structure	50	1,171	165	2014	Cluster1	Concerns
Relationship	Relationship & trust	51	1,017	114	2015	Cluster3	Concerns
Network structure	Market structure	47	758	97	2015	Cluster1	Concerns
Stability	Stability	50	739	92	2014	Cluster1	Concerns

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Default	Default & failure	49	776	88	2014	Cluster1	Concerns
Failure	Default & failure	50	751	80	2012	Cluster1	Concerns
Loss	Default & failure	47	583	72	2015	Cluster1	Concerns
Network model	Market structure	45	417	51	2015	Cluster1	Concerns
Contagion risk	Contagion & systemic risk	35	402	45	2013	Cluster1	Concerns
Interbank exposure	Contagion & systemic risk	38	426	43	2013	Cluster1	Concerns
Financial contagion	Contagion & systemic risk	35	373	40	2016	Cluster1	Concerns
Linkage	Market structure	45	327	40	2013	Cluster1	Concerns
Network topology	Market structure	44	336	40	2015	Cluster1	Concerns
Financial stability	Stability	44	336	36	2013	Cluster1	Concerns
Resilience	Stability	43	340	33	2016	Cluster1	Concerns
Inter-connectedness	Market structure	41	240	30	2017	Cluster1	Concerns

APPENDIX B: BIBLIOMETRIC MAPS AFTER APPLYING ExC5

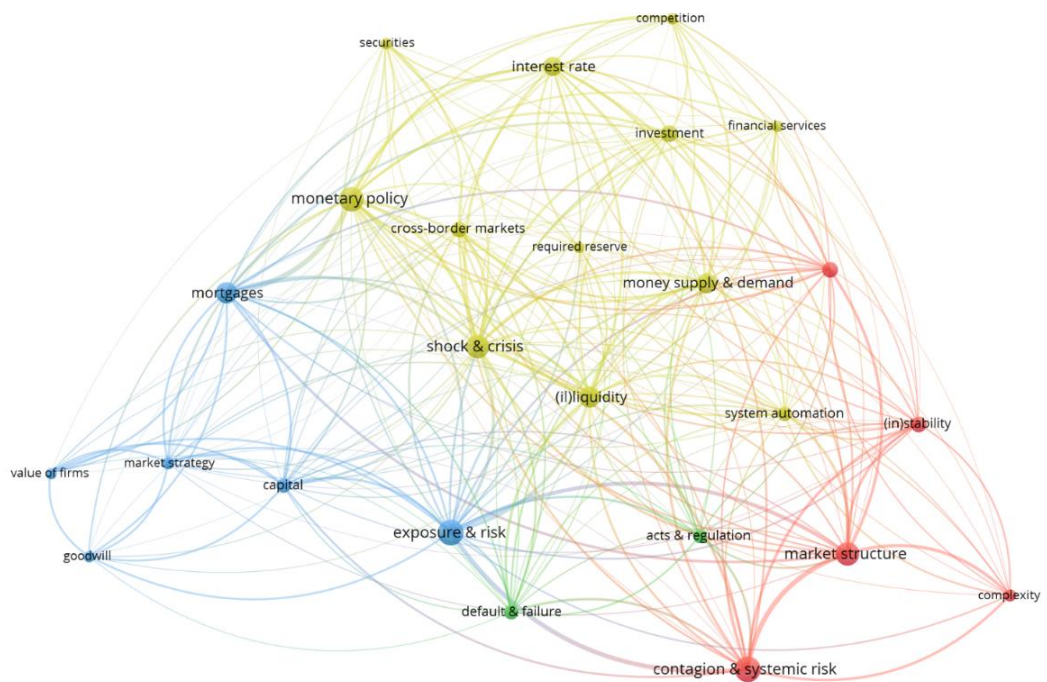


Figure B.1. Clusters resulting from the keywords co-occurrence analysis (ExC5 applied).
The figure shows the clustering of frequent keywords of the documents in the case where ExC5 is applied.

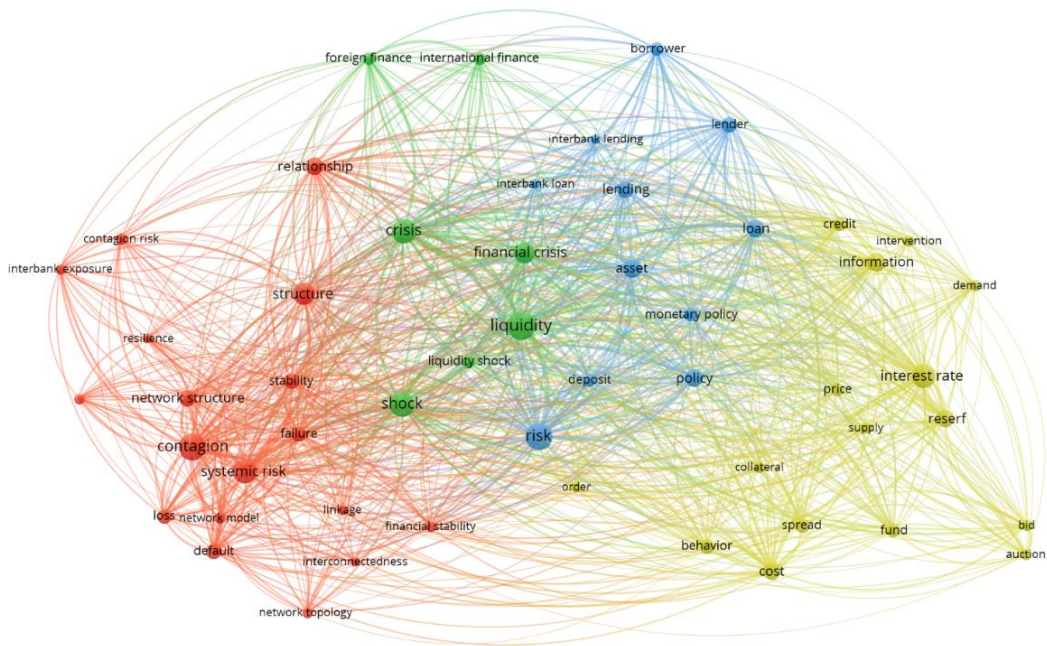


Figure B.2. Clusters resulting from the terms co-occurrence analysis (ExC5 applied). The figure shows the clustering of frequent terms from the title and abstract of the documents in the case where ExC5 is applied.

APPENDIX C: THE QUALITY CHECKLIST

The research team evaluated and scored the four quality criteria for each publication based on the guidelines provided in the checklist shown in Table C.1.

Table C.1. Quality checklist. The table lists the criteria applied for the quality assessment of documents.

#	Criterion	Description
1	Problem and motivations	(1): Neither problem statement nor hint of motivation; (3): Implicit problem statement and hint of motivation; (5): Explicit problem statement and hint of motivation; (2) & (4): Intermediate modes
2	Context and method	Average of reference score * and method score ** that are given as follows: * (1): $n < \mu - \sigma$; (2): $\mu - \sigma < n < \mu$; (3): $n = \mu$; (4): $\mu < n < \mu + \sigma$; (5): $n > \mu + \sigma$; where n denotes the number of references used by the publication, μ is the mean number of references (=39), and σ is the standard deviation of references (=17) ** (1): No specific method/model, (3): Method/model described but not in a separate section, (5): Separate section for the method/model description, (2) & (4): Intermediate modes
3	Data and results	(1): No explanation of data and findings; (2): Poor explanation of data or findings; (3): Strong explanation of data or findings without explaining the other, or poor explanation of both; (4) Strong explanation of data or findings with poor explanation of the other; (5): Strong explanation of both data and findings
4	Limitations and directions	(1): No futures studies and limitation; (2): Poor futures studies or limitation; (3): Strong futures studies or limitation without the other, or poor both futures studies and limitation; (4): Strong futures studies or limitation with poor the other; (5): Strong both futures studies and limitation

APPENDIX D: EVOLUTION OF BALANCE SHEET ITEMS

The amount of balance sheet operations of each bank i in each time step t changes according to the equations in Table D.2.

Table D.2. Equations for updating banks' balance sheet operations. The table lists the equations applied to update the banks' balance sheet at each time step.

#	Operation	Equation
1	Clients' term deposit update	$d_{i,t} \sim \mathcal{N}(\mu_{d_{i,t-1}}, \sigma_{d_i}^2)$
2	Clients' demand deposit update	$d'_{i,t} = d'_{i,t-1} - \sum_{j \in Payer_{i,t}} p_{i,j,t} + \sum_{j \in Payer_{i,t}} p_{j,i,t}$ <p style="text-align: center;">in which</p> $p_{i,j,t} \sim \mathcal{N}(\mu_{p_{i,t-1}}, \sigma_{p_i}^2) \times \mathbf{P}$ <p style="text-align: center;">\mathbf{P}: random binary matrix</p>
3	Interbank debt update	$b_{i,t} = b_{i,t-1} - \sum_{j \in Lenders_{i,t} \mid T < t} repay_{i,j,t} + \sum_{j \in Lenders_{i,t}} loan_{i,j,t}$ <p style="text-align: center;">in which</p> $\sum_{j \in Lenders_{i,t}} loan_{i,j,t} \leq Liq_{i,t}^{def}$ $Liq_{i,t}^{def} = \begin{cases} NCOF_{i,t} - HQLA_{i,t}, & LCR_{i,t} < 1 \\ 0, & \text{otherwise} \end{cases}$ $HQLA_{i,t} = r_{i,t} + s_{i,t} + \min \left[0.85l_{i,t}, \frac{2}{3}(r_{i,t} + s_{i,t}) \right]$ $NCOF_{i,t} = XF_{i,t}^- - \min[XF_{i,t}^+, 0.75XF_{i,t}^-]$ <p style="text-align: center;">$XF_{i,t}^-$ and $XF_{i,t}^+$: the expected cash outflows and inflows</p>
4	Central bank fund update	$f_{i,t} = \begin{cases} Liq_{i,t}^{def} - \min(b_{i,t-1}, s_{i,t}), & Liq_{i,t}^{def} > b_{i,t-1} \text{ and } s_{i,t} > 0 \\ 0, & \text{otherwise} \end{cases}$
5	Securities update	$s_{i,t} = \begin{cases} s_{i,t-1} + [\lambda \sim \mathcal{U}(0,0.15)] Liq_{i,t}^{exc}, & Liq_{i,t}^{exc} > 0 \\ s_{i,t-1} - f_{i,t}, & Liq_{i,t}^{def} > 0 \end{cases}$
6	Securities pledged	$s'_{i,t} = s'_{i,t-1} + f_{i,t} - repay_{i,CB,t}$
7	Clients' credit update	$c_{i,t} \sim \mathcal{N}(\mu_{c_{i,t-1}}, \sigma_{c_i}^2)$

8 Interbank claim update
$$l_{i,t} = l_{i,t-1} - \sum_{j \in Borrowers_T | T < t} repay_{j,i,t} + \sum_{j \in Borrowers_t} loan_{j,i,t}$$

in which

$$\sum_{j \in Lenders_t} loan_{i,j,t} \leq Liq_{i,t}^{def}$$

$$Liq_{i,t}^{exc} = \begin{cases} HQLA_{i,t} - NCOF_{i,t}, & LCR_{i,t} > 1 \\ 0, & \text{otherwise} \end{cases}$$

9 Reserve balance update $r_{i,t} = r_{i,t-1} +$ the result of the following operations considering their positive or negative impact:

- Settlement of the clearing vector (+ or -)
- Principal of client's credit received (+)
- Principle of term deposit withdrawn (-)
- Funds borrowed from the CB or other banks (+)
- Debts repaid to the CB or other banks (-)
- Loans repaid by other banks (+)
- Purchase of securities (-)
- Earning from the fire sale (+): $(1 - \lambda_{s_{i,t}})\varphi_{s_{i,t}}s_{i,t} + (1 - \lambda_{c_{i,t}})\varphi_{c_{i,t}}c_{i,t}$ where $\lambda_{s_{i,t}}, \lambda_{c_{i,t}} \sim \mathcal{U}(0,0.15)$, and $\varphi_{s_{i,t}}$ and $\varphi_{c_{i,t}}$ denote the quantity sold of securities and clients' credits, respectively

10 Equity update $e_{i,t} = e_{i,t-1} +$ the result of the following operations considering their positive or negative impact:

- Profit received on client's credit (+)
- Interest paid on term deposit (-)
- Interest paid to other banks on the interbank loan (-)
- Interest paid by other banks on the interbank loan (+)
- Loss from the fire sale (-): $\lambda_{s_{i,t}}\varphi_{s_{i,t}}s_{i,t} + \lambda_{c_{i,t}}\varphi_{c_{i,t}}c_{i,t}$