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THE ROLE OF PAYMENTS IN DIGITAL FINANCE

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Abstract

This thesis investigates the role of payment in digital finance through a collection of papers that delve into theoretical, empirical, and policy-centric aspects. The first paper sets the thesis in the domain of policy-relevant research and connects the literature on digital finance with current policy discussions. The review covers topics such as technology-based lending, distributed ledger technology, and the impact of emerging technologies on supervisors' practices. It highlights the need for collaborative efforts between academia and supervisors to propel future research. The second paper analyses the impact of open banking policy on financial intermediaries. It examines the effects of open banking frameworks on loan interest rates and emphasizes the role of regulators in mitigating challenges. The third paper investigates the role of payments in financial intermediation, especially during the COVID-19 pandemic. It highlights the impact of payment systems on systemic risk and emphasizes the importance of an optimized capital structure and timely government intervention in averting liquidity shocks. In conclusion, this thesis offers nuanced insights into digital finance, covering policy implications, open banking frameworks, and systemic risk dynamics. It provides a comprehensive understanding of the evolving financial landscape and is relevant to academic discourse and policy-makers.

Contents

Introduction

This thesis studies the role of payments in the digital finance evolution that, over the last decades, has been characterizing the financial innovation. The thesis is structured as a collection of papers that investigates the theoretical ground of the literature on financial intermediation, the empirical analysis, and relative policy-relevant implications. Starting with the first paper that connects the literature on digital finance with policy debates, this thesis is positioned within the stream of policy-oriented research. Specifically, this article provides an extensive review of the expanding literature on digital finance, with a focus on studies that demonstrated to be relevant to policymakers. The review examines four primary areas in detail. First, it investigates the role of technology-based lending, including policies related to Fintech, BigTech, and Open Banking. Secondly, it delves into the adoption of distributed ledger technology and its impact on financial analysis, including the economic functions of blockchain, decentralized finance (DeFi), and the development of Central Bank Digital Currencies (CBDCs). Then, the review explores the transformative impact of emerging technologies on supervisors' practices. Each section is firmly grounded in economic theory, supported by empirical analysis, and relevant for ongoing policy deliberations. Ultimately, the paper highlights the need for collaboration between academics and supervisors to drive future research initiatives in the realm of digital finance. The second paper responds to the gaps in the literature on digital finance related to policy-relevant research. Indeed, this study explores the impact of open banking frameworks on financial intermediaries. The frameworks promote data-sharing policies that aim to reduce friction in information asymmetry, enhance market competition, and promote financial innovation. The study uses a difference-in-differences approach to examine the effect of open banking adoption on traditional financial intermediaries in the European syndicated loan market. The results show that introducing open banking frameworks significantly reduces loan interest rates without affecting collateral. However, the regulatory fragmentation in enforcing data-sharing policies, and the specific characteristics of syndicated loans limit the positive effects of data portability and interoperability competition. This finding highlights the crucial role of regulators in establishing financial innovation policies, and emphasizes how private information continues to play a significant role in the syndicated loan structure. The final paper analyses the role of payments in financial intermediation in a more traditional context, investigating its relationship with systemic risks. This study examines the relationship between Payment Statistics Relevant Institutions (PSRIs) and the characteristics of banks in the context of the COVID-19 pandemic. The study uses an empirical cross-sectional analysis of 101 systemic institutions to investigate systemic risk propagation, and explains the two dimensions of the financial contagion effect. First, the research shows that PSRIs amplify the unique characteristics of banks, which typically affect systemic risk. The analysis considers the overall impact of COVID-19 on banks' market performance and liquidity structure. Secondly, the paper investigates the relationships between commercial and market-oriented banks as channels for transmitting economic distress during the pandemic. The results suggest that PSRIs are a valuable additional measure for assessing systemic risk centrality. Additionally, the study highlights that an optimized capital structure and timely government intervention can act as mitigating factors against significant liquidity shocks in the interbank market. If unaddressed, such shocks have the potential to trigger cascading effects within the banking sector. In conclusion, this thesis contributes to providing a comprehensive understanding of the role of payment in digital finance by jointly considering several aspects. By covering policy implications, open banking frameworks, and systemic risk dynamics, the thesis offers nuanced insights that are relevant to the academic and policy discourse.

Break on through (to the other side) of digital finance

Nico Lauridsen*

Abstract

This article reviews the growing literature on digital finance analysis policy-relevant research. It covers multiple areas of this emerging field that are becoming priorities for policymakers. The literature review focuses on four primary areas. First, it looks at the role of technology-based lending, including Fintech, BigTech and Open Banking policy. Secondly, it discusses the adoption of distributed ledger technology and its impact on finance analysis, including the economic function of blockchain, decentralised finance (DeFi) and the development of Central Bank Digital Currencies (CBDCs). The last part of the review discusses how emerging technologies are changing supervisors' practices. All sections are grounded in economic theory, supported by empirical analysis, and relevant to policy debates. In the end, the paper highlights the need for collaboration between academics and supervisors to develop future research in digital finance.

Keywords: Financial innovation, Digital Finance, FinTech, Open Banking, BigTech, Blockchain, DeFi, CDBCs, Bank supervision

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1. Introduction

The paper analyses the state-of-the-art literature on digital finance, providing policy-relevant insights and bridging with ongoing regulatory and supervisory discussions. This literature has been rapidly growing in line with the speed of technological advancements pushing the evolution of the financial sectors. The complexity of this phenomenon, which has involved all aspects of the financial system, is reflected in the theoretical and empirical literature on financial intermediations. Digital finance has become a crucial priority for regulators and supervisors worldwide, who have acknowledged the importance of addressing the risks associated with technology and leveraging the opportunities it offers. Unlike previous literature reviews that have limited their study to specific aspects of digital finance within an academic perspective, this study takes a comprehensive approach to digital finance, grounded in regulatory and supervisory priorities (Thakor, 2020; Boot et al., 2021; John et al., 2022; Hirtle and Kovner, 2022; Berg et al., 2022; Auer et al., 2022; John et al., 2023). This different approach contributes to the literature by giving a comprehensive overview of academic papers that have a policy-relevant angle. Furthermore, the paper discusses potential areas of future research where policy analysis and academic works could be bridged, which could significantly impact ongoing debates on digital finance, going deeper into discussing empirical challenges and limitations.

From a methodological standpoint, the literature review used the list of journal analyses by Auer et al. (2023) to identify papers related to digital finance that are relevant for policy-makers. This list ranks research based on its policy relevance, and calculates impact factors using only citations in central bank publications. The ranking shows that most policy-relevant papers come from journals in economics, while major finance journals are less likely to have policy-relevant papers. These results are driven by research in traditional areas such as monetary policy, macro-finance, and other related fields that could be applied to the economics literature. However, this limitation should be contextualised within the literature on digital finance to see if it is still consistent. Future developments of this analysis should investigate which aspects of digital finance are more relevant between economic and finance journals, e.g. central bank digital currencies would likely be relevant to economic journals. At the same time, FinTech lending would be more relevant to finance journals. Additionally, it should be included in the systemic literature review based on the ranks of papers in Appendix 1.

The structure of the paper is based on the main areas related to digital finance: (i) from data to lending that include Fintech and BigTech lending, Open Banking; (ii) From Blockchain to Decentralised Finance (DeFi) and CBDCs; (iii) Cybersecurity Risk; (iv) SupTech. All sections are grounded in economic theory, supported by empirical analysis, and relevant to policy debates.

The first part analyses the stream of the literature that looks at the rapid development of FinTech and BigTech lending concerning the use of data in providing financial products and the customers' welfare implications. It highlightes that this new era of financial innovation is changing how financial products are provided through digital channels. This part of the literature is strongly founded in the information asymmetries theory that has characterised banking and finance research and contributed to explaining the effect of technology on lending activities. Furthermore, this section discusses the more recent studies that analyse the implications behind open banking frameworks and the role of regulators in facilitating financial innovation and taking novel sources of risk that come with this evolution of the financial sector. The second part considers distributed ledger technology as the paradigm shift in finance. Firstly, it presents the different consensus mechanisms behind the blockchain, and the economic functions associated with DeFi. Secondly, it discusses the challenges in designing regulatory frameworks for crypto-assets and supervisory enforcement in micro and macro-prudential activities. Finally, the last part of this section is dedicated to the recent debate surrounding the design and adoption of Central Bank Digital Currencies (CBDCs), including their potential implications for the financial infrastructure. The third part analyses the recent cybersecurity risk literature based on the theoretical elements of systemic risk and propagation of contiguous network dynamics and the potential consequences for market integrity and financial stability. The fourth and last section of the paper shifts focus from the impact of technology on financial intermediaries to the impact of emerging technologies on supervisors' practices, with specific attention to literature on the effects of banking supervision on market risk-taking.

This literature review highlights some common aspects of this fourth stream of research. Indeed, the empirical challenges related to the lack of data to push forward the literature stress by Goldstein et al. 2019 are important factors that have limited the growth of research in this field.. The need for more research that uses property data and novel methodology analysis of large datasets is still present. It is important to note that this particular source has limited access. Therefore, it is necessary to carry out joint research projects and encourage collaboration among academia, supervisory authorities, and industry, with a common approach. Academia requires both supervisory and industry data to advance its research, while supervisors need academia to improve their methodology analysis, and industry requires a better understanding of future market developments. Similarly, the industry needs academia and supervisors to participate in policy debates and stay up-to-date with the latest trends and research. In the end, digital finance is just another step in the evolution of financial systems. However, the speed of change requires a collaborative effort in addressing the market, regulatory and supervisory challenges of a new wave of financial innovation. The paper unfolds as follow: New era of financial innovation: From data to lending; From blockchain to DeFi and CBDCs; Cybersecurity risk; SupTech: a banking supervision prospective; Conclusion and policy implication.

2. New era of financial innovation: From data to lending

This section discusses the changes in financial innovation and what is fundamentally different from the past, making it relevant for policymakers. The following paragraph delves into the connection between economic theory and the role of information in financial intermediaries. It also discusses how technology affects the relationship between borrowers and lenders from three angles: FinTech and BigTech lending, and open banking.

Technological advancements have brought about a revolutionary change in the financial sector. Over the past two decades, we have witnessed a significant transformation in how financial intermediaries operate in the market. With the availability and portability of data, information structure and flow have undergone a massive shift, affecting every aspect of economics. This has been further facilitated by the emergence of new technology, such as artificial intelligence and blockchain, which can efficiently process information into data. This transformation has significantly impacted how goods and services are provided and priced, reshaping competition among agents, influencing the valuation of financial assets, determining how businesses expand, and even affecting concepts of privacy and market structures themselves (Veldkamp, 2023; Veldkamp and Farboodi, 2023). The rise of the digital economy has highlighted the significance of data in financial intermediation. Digitised information, as data, has become a fundamental asset and raw material for financial intermediaries that can drive market efficiency in financial innovation. What sets the present apart from the past is how financial products and services are provided.

The following three sections analyse the rise of technology-based lending by new players in the market, such as Fintech and BigTech, and the respective regulatory frameworks where these players are often subject to fewer regulations than traditional financial institutions (TradFin). First, it focuses on the different implications behind the use of technology in providing lending activity to the market. This part discusses the welfare implications and the related regulatory and supervisory issues and challenges. Second, the literature discussion continues with analysing the more direct regulatory aspect involving open banking frameworks. Recent research focuses on the impact of data-sharing regulations on financial intermediation activities, showing policy-makers' role in supporting and facilitating financial innovation.

Before starting to dive into this fast-evolving literature, it is crucial to understand the theoretical base where this stream of research is grounded. This fundamental transformation or evolution of the financial sectors is strongly founded in the information asymmetries theory that has characterized the banking and finance literature (Akerlof, 1970). Information asymmetry, extensive theoretical literature has modeled and argued the credit relationship, considering ex-ante and ex-post on moral hazard and adverse selection issues of the lending activities. Banks have struggled to assign and observe borrowers' behaviors over time, raising information imperfection that affects market effectiveness and equilibrium. This literature considers information asymmetry as an exogenous component of the market structure. Under this theoretical approach, it has been shown that threat credit rationing could reduce borrower moral hazard problems, highlighting how ex-ante evaluation is influenced not only by the demand for capital but also by the risk-taking of the borrowers. (Stiglitz and Weiss 1981). The ability of banks to acquire and monitor information becomes an essential competitive advantage in lending activities (Sharpe, 1990; Rajan, 1992; Boot & Thakor, 2000). Therefore, technological improvements can lead to better information processing and low-cost or free access to information that generates spillover effects, ultimately benefiting customers by increasing market competition (Pagano and Jappelli, 1993; Hauswald and Marquez, 2003). Theoretical literature on information asymmetry has been turned into empirical studies that analyse the friction between soft and complex information in transactional and relationship lending. Many studies have examined the difference between relationship lending, where access to credit is determined by uncodified soft information, and transactional lending, where structured data, or hard information, can automate lending. Small banks seem to have a competitive edge in lending based on soft information and financial constraints on small businesses (Berger et al., 2005). Furthermore, geographical proximity is one of the main ways to reduce the opacity of private information.

However, credit-scoring technology is only able to capture partial soft information. Small institutions that leverage soft information by providing liquidity insurance in the market have a competitive advantage that remains valid during periods of financial distress. The dichotomy between soft and hard information is changing with the development of emerging technology that leverages the mass of data generated in the last decade. Emerging technologies have enabled the encoding of soft information within hard information, leading to some financial intermediation theories needing to be re-written. This has opened the space in the literature to new streams that leverage this theoretical background to study the peculiarity of FinTech and BigTech lending.

From a policy perspective, the emergence of the data economy in the financial system has also brought new risks associated with technology-driven business models. When these novel source risks that often come from cybersecurity and data protection issues are combined with traditional risks associated with financial intermediation, it can increase the exposure to financial instability and market integrity (Aldasoro et al., 2022). In other words, risks such as liquidity, outsourcing, systemic, concentration, operations, and legal could be threatened by cyber-attacks, data bridges, and abuse. At the same time, the emergence of new risks highlights a regulatory challenge in creating new frameworks that balance market competition and financial stability while also addressing the threats posed by technology-based business models. This is particularly important in supporting financial innovation in the traditional trade-off between market competition and financial stability (Feyen et al., 2021). Indeed, financial innovation regulatory frameworks should not only focus on efficiency and competition but also include data privacy and customer protection as a crucial third dimension, which affects financial stability and market integrity (Chen et al., 2021). Data availability and portability are important drivers of financial innovation and market efficiency, but the digitisation process also carries cyber risks (Crosignani et al., 2023). Possible data manipulation or algorithmic abuse could threaten financial stability and integrity (Fuster et al., 2022; Chen et al., 2023). Regulatory interventions have tried to balance these three dimensions of facilitated financial innovation, which is an important endogenous force for economic growth (Leaven et al., 2015). The regulators to cover emerging risk from technologies and business models have initially apply the principle same risk, same rule using regulatory bodies. However, the fundament different of FinTech and BigTech from TradFin have created a mismatch between the application of entity-based regulation design for TradFin and the new players. The hight specializations of fintech business models and the non-financial nature of BigTech have shown the limits of entity-based regulation in taking care of emerging risks into financial innovation and how their can create significant barriers to the future development of financial innovation. To cover emerging risks from technologies and business models, regulators have initially applied the principle of the same risk, the same rule using regulatory bodies. However, the fundamental differences between fintech and big tech from TradFin have created a mismatch between the application of entity-based regulation design for TradFin and the new players. The highly specialized nature of FinTech business models, coupled with the non-financial nature of BigTech, has highlighted the limitations of entity-based regulation in addressing emerging risks in financial innovation. The application of regulatory bodies that were not designed explicitly for FinTech entities could hinder the progress of financial innovation in the future. This may lead to an over-regulated fintech industry during its startup phase, ultimately stifling innovation and progress (Chen at al., 2019). To facilitate innovation, regulators have designed regulatory sandboxes and innovation hubs to create a safe space to test innovation (Cornelli et al., 2023). At the same time, there has been a shift in regulatory approach from entity-based to function-based regulation (Borio et al., 2022). This means that regulators focus on specific risks associated with new business models and emerging technologies instead of regulating entities. This approach allows for a more tailored and flexible regulatory framework that can adapt to the rapidly evolving technological landscape. Nevertheless, financial innovation is entering a phase where regulations will play a crucial role in determining the future of development, defining new rules and frameworks designed to take care of the risk and facilitating innovation. The section continues with additional insights for the literature review on Fintech and BigTech lending and open banking.

2.1. Fintech lending

This stream of the literature can be divided into two logical blocks. The first is related to the screening and monitoring capabilities of Fintech lending technology, which funds a strong foundation in the information asymmetry theory previously discussed. The second one focuses on the welfare implications of FinTech lending and the possible heterogeneity effect on lenders. FinTech can be defined as a technology-based business model that delivers financial products and servers via digital channels (BIS 2018; FSB 2019). More specifically, FinTech lending can be delineated by either the manner of customer–lender interaction or the technological approaches employed in screening and monitoring borrowers. In terms of customer–lender interaction, FinTech lending is characterized by processes conducted solely through apps or online platforms (Buchak et al., 2018; Fuster et al., 2019). In detail, this approach reduces processing times and operational costs and enhances the overall user experience, providing greater adaptability to demand fluctuations and minimizing errors arising from human interactions. Notably, this mode of lending may appeal particularly to borrowers prioritizing convenience over personal advice. On the other hand, when focusing on screening and monitoring technology, FinTech lending is identified by adopting technologies that enhance TradFin in assessing and overseeing borrowers. These technologies, such as digital footprints or machine learning algorithms, can broaden the scope of available information or improve the quality of existing information (Berg et al., 2020; Fuster et al., 2022). Consequently, such technological applications can significantly impact default and recovery rates, modify pricing and non-price terms, and influence the inclusivity of borrowers accessing financial services. This dual perspective underscores the transformative role of technology in reshaping lending processes and adapting them to the evolving needs of both lenders and borrowers within the FinTech landscape. The emergence of FinTech lending is not only due to technological advancements in screening and monitoring but also to regulatory arbitrage, including shadow banks. The regulatory restrictions on traditional banks after the 2007-09 crisis have reduced mortgage lending, which has created an opportunity in the market for FinTech and shadow banks (Irani et al., 2021; Bao and Huang, 2021). The market share of Fintech lenders has experienced significant growth, expanding from approximately 3% in 2007 to 12% in 2015. This increase represents a significant portion of the overall growth in the market share of shadow banks during that period (Buchak et al., 2018). This trade was consistent during the pandemic, with FinTech companies taking the lead in expanding access to credit for individuals facing financial constraints. This was a commendable move, but the sustainability of this trend is uncertain, given the threefold increase in delinquency rates for FinTech loans following the outbreak. However, borrowers holding both types of loans prefer repaying bank loans first, highlighting the importance of trust and reliability in financial institutions, especially during times of uncertainty (Bao and Huang, 2021).

The literature on scoring and monitoring FinTech lending emphasizes the importance of data in determining creditworthiness and access to credit. This data is often derived from payment records. Banks use private data to assess creditworthiness, and historical payment data can help them screen borrowers more effectively. Internal ratings can also capture private information through payment data and reduce the default probability rates of loans (Berg, 2015; Puri et al., 2017). This evidence from TradFin emphasises that FinTech lending determines an important competitive advantage in the market by using emerging technologies in processing data. The role of private data in credit scoring technology has been considered, and it has been shown how digital footprints in e-commerce are reliable predictors of default rates, which can improve information on credit bureau scores (Berg et al., 2020). This effect of technology in FinTech lending has led to a faster and more efficient process of mortgage applications, without compromising on the quality of lending or resulting in higher defaults. Compared to TradFin, FinTech lenders are more adept at adjusting their supply in response to external mortgage demand shocks, mainly targeting borrowers who have limited access to finance. This has made the process of obtaining a mortgage much more accessible and convenient for individuals who have traditionally struggled to secure loans through traditional channels (Fuster et al., 2019; Vallée and Zeng, 2019). However, FinTech lenders still have less data than TraFis facing higher information asymmetries resulting in lower credits scores and higher default rates (Chava et al., 2021). This dyscrasia between information structures results in FinTech lending in loans with higher credit scores and lower debt-to-income ratios than traditional lenders. Fintech lenders also charge these more creditworthy borrowers lower interest rates. This evidence provides insights into the lending practices of fintech lenders and highlights the potential trade-offs between credit access and risk management in the fintech market (Di Maggio and Yao, 2021). Furthermore, Maggio et al., (2023) analysed the "buy now pay later" (BNPL) model and found that it has a positive impact on consumers by increasing their access to credit and spending levels. This leads to an increase in the retail share of total spending. These effects are too significant to be explained by standard intertemporal and static substitution effects. Additional evidence shows that merchants can benefit from using BNPL to improve sales. Payment defaults on BNPL only inflict moderate costs, and the benefits of offering BNPL significantly outweigh the costs for the merchant (Berg et al., 2023).

A recent development in the literature has been the exploration of the welfare implications of FinTech. It is crucial to acknowledge that the socio-economic context plays a significant role in determining the impact of FinTech lending. In particular, the ability of FinTech lenders to provide access to credit to individuals who are typically excluded from traditional lending in developing economies has and enabling economic growth in previously underserved communities expanded the reach of non-traditional lending. This has the potential to bring about positive changes by improving financial inclusion (Jack and Suri, 2014; Suri et al., 2021; Tantri, 2021). It has been observed that the use of technology-based lending with algorithmic decision-making in advanced economies can lead to discrimination against Black and Latino minorities (Bartlett et al., 2022; Fuster et al., 2022). This discrimination can be attributed to several factors, such as the enhanced accuracy of the technology in identifying the relationship between observable factors and default outcomes, its improved ability to triangulate borrowers' identities, and its effectiveness in identifying borrower groups with elevated default probabilities, even after accounting for observable variables. The technology may impose penalties on these groups to account for their higher risk of default beyond the predictions based on the structural relationship between other observable factors and default outcome. Such discriminatory effects of algorithmic decision-making can have severe implications and need to be addressed to ensure a fair and equitable lending system for all. Asymmetric information within FinTech lending can have significant repercussions, resulting in welfare losses and notable price distortion. This is primarily due to the inherent asymmetry of information. However, it is worth noting that the distortion in equilibrium quantities remains relatively modest, thanks to the inelastic demand exhibited by borrowers (DeFusco et al., 2022). The welfare implication discussed here pertains to the unequal access to technology courses, which also contributes to the gender gap in accessing financial services. Simply introducing new technology cannot bridge this gap. Moreover, the current disparity in access to financial services offered by traditional financial institutions is unlikely to reduce as these institutions increasingly shift to digital platforms. However, policies aimed at promoting financial inclusion through fintech will need to address the reasons behind the fintech gender gap (Chen et al., 2023).

This literature on Fintech lending has been studied extendedly from a micro perspective, focusing on the role of payment data in providing credit through digital channels. However, future research should consider the impact of this novel form of lending from a macro angle. Fintech lending could significantly impact transmitting monetary policy as a complementary channel from traditional ones (Cornelli et al., 2023). Furthermore, as the literature has shown, analysing the welfare impact from different socioeconomic contexts can provide significant contributions (Jack and Suri, 2014; Suri et al., 2021; Tantri, 2021). Indeed, this should also be linked to the respect of regulatory frameworks. Bridging academic research and policy is pivotal for studying the impact of upcoming regulations with different objectives and goals based on the policy priority of the authorities enforcing the frameworks. In this context, it would be relevant to study the fundamental difference between horizontal regulatory frameworks that do not come from financial systems authorities, such as AI, and vertical ones that are designed for specific financial sectors, like open banking, which is discussed in the following section.

2.2. BigTech lending

This section, different from what has been discussed previously on financial innovation, considers the effect and the policy implication from the entrance of large technology companies or BigTechs into the financial market. These companies are increasingly entering the finance industry and transforming financial markets. Due to their unique business models, companies like Alibaba, Amazon, Meta (Facebook), Alphabet (Google), and Tencent have access to a large stock of user data. This access to user data allows them to offer various financial services, such as payments, money management, insurance, and lending. The non-financial nature of BigTechs based the strong IT legacy systems have characterized their business models on Data-Network-Activity (DNA) feedback loop. These three elements of the BigTech DNA characteristics are interconnected and reinforce each other. Network externalities allow these companies to generate more data, which is the key input into data analytics. Analysing large amounts of data enhances their existing services and attracts more users. In turn, more users provide the critical mass of customers required to offer a wider range of activities, which leads to even more data. BigTechs moved into the financial market, mainly in the payments segment, to close and improve the DNA loop with high-frequency transactional data to provide additional financial products such as lending to maintain customers within the platform (Forst et al., 2019; Doerr et al., 2023). This peculiarity of the BigTechs underlines different financial innovation aspects with important policy-relevant issues. This peculiarity of the BigTechs underlines different financial innovation aspects with important policy-relevant issues. However, the research and literature on BigTechs are still limited and underdeveloped due to the lack of property data. Initial evidence has shown that the development BigTech credit is more pronounced in countries with higher GDP per capita, albeit at a diminishing rate and higher banking mark-ups, along with less stringent banking regulations (Cornelli et al., 2023). At the same time, analysis with more granular data has shown that BigTechs credit responds strongly to firm-specific attributes such as transaction volumes and a network score utilized for calculating firm credit ratings. This underscores that BigTechs credit outperforms in terms of defaults and firm performance in ex-post evaluations. These findings are particularly significant for the macroeconomic landscape, especially concerning the monetary transmission mechanism. They suggest that the provision of BigTechs credit tends to diminish the effectiveness of the use of collateral since credit provision becomes less dependent on asset price fluctuations (Gambacorta et al., 2023). Furthermore, establishing a digital payment footprint enables firms to avail themselves of various financial services and products big tech firms provide. It also triggers spillover effects on bank credit by utilising big tech financial services and transaction data generated via QR codes. Integrating BigTech credit into the credit registry enhances banks' screening and monitoring capabilities, particularly in assessing small and medium-sized enterprises (Beck et al., 2022). The impact of monetary policy transmission on BigTechs has been a subject of interest in the literature. BigTechs exhibit a heightened responsiveness on the extensive margin, even when accounting for credit demand. This effect is more prominent during periods of monetary easing than tightening, especially for larger firms with greater network centrality. The contrast between BigTech and TradFin is more evident among online and offline sellers. Moreover, this difference is more pronounced when comparing BigTech credit with secured than unsecured bank credit. These findings suggest that the information advantages and risk management models employed by BigTech lenders amplify monetary policy transmission (Haung et al., 2023). However, the preliminary evidence in the literature comes mainly from China, showing the limitations of the results. Indeed, future works should consider extending the analysis to other socio-economic contexts and regulatory frameworks to investigate candidates for these results and policy implications. BigTech companies are currently operating in a regulatory grey area, taking advantage of non-financial business activities that fall outside the scope of existing regulatory bodies. They also benefit from the international financial structure, which allows them to engage in regulatory arbitrage. However, regulators and supervisors need to consider the financial stability and integrity risks that arise from providing crucial cloud services to financial institutions and controlling non-financial data. This presents an additional challenge for regulators who must consider systemic relevance, cross-intragroup interdependence, and network externality arising from financial and non-financial products. To address this, a possible regulatory framework for BigTech companies should combine activity-based and entity-based regulations to match risk sources with corporate entity structures, covering financial and non-financial risk exposure. Indeed, this approach considers the current regulatory perimeter in designing additional frameworks within the intragroup and governance structure (Ehrentraud et al., 2022).

In the end, the risk of regulatory capture by the speed of innovation is still high under different approaches. It underlines how regulatory and supervision collaboration is needed to develop future frameworks that are more modular and adaptable to different technologies. Future research in this stream of the literature on the possible monopoly issues of non-financial data and the relation between systemic exposure and cyber threat would be fundamental in developing regulatory frameworks. These cyber-risk aspects are be discussed in more detail in the dedicated sessions.

2.3. Open Banking: data-sharing in financial intermediaries

This section goes further from the previous discussion regarding the various impacts of financial innovation on lending activities resulting from market actions. It presents an analysis of the role of the open banking framework as a sharing policy that enables financial innovation. The open banking framework constitutes a two-sided market wherein establishing standards and regulations regarding data-sharing involves both TradFin and FinTech entities. This goes beyond simply sharing payment data with external entities, as it also includes ensuring mutual interpretability among all stakeholders. The success of data-sharing policies relies on the benefits that both parties receive. Regulatory bodies and supervisory authorities advocate for open banking frameworks that utilize application programming interface (API) technology to create a secure data-sharing infrastructure, promoting market competition and providing access to financial services. Different jurisdictions have approached the design and implementation of open banking policies in various ways, highlighting that the exploration of financial intermediation data is still in its early stages. Developing countries utilize open banking to improve financial inclusion, while in Europe, policies are introduced to reduce barriers to market entry for fintech companies, encouraging financial innovation. Regardless of policy objectives, the development of open banking frameworks faces shared challenges and obstacles, emphasizing the crucial role of regulation in creating enabling technological infrastructure for data-sharing.

The study of open banking literature is rooted in theoretical explorations of the relationship between payment data and lending, specifically in the context of data-sharing policies. These investigations have focused on the open banking model, analysing the impact of data-sharing policies on the credit market and highlighting the crucial role of data as a driving force for financial intermediation. Parlour et al. (2022) have shed light on the effect of open banking on innovation within payment processors and financial service providers, emphasizing that policy adoption has increased competition in the payment service sector, leading to lower customer service costs. The data-sharing mechanism plays a crucial role in shaping competition within the credit market, particularly when borrowers own their financial data and share them with third-party lenders to access a broader range of novel credit options (He et al., 2023). In open banking, data sharing is a vital catalyst for the growth of fintech firms, facilitating their entry into the market and underscoring the importance of customer data as a driver of financial innovation (Babina et al., 2022). Initial empirical evidence on the impact of open banking comes primarily from the fintech sector. It has been shown that borrowers with higher risk levels and lower credit scores are more likely to share their data, resulting in increased loan approval rates and lower interest rates (Nam, 2023). However, regulatory frameworks for open banking must be tailored to each country specific needs, considering market conditions and technological infrastructure at different stages of development, to achieve policy objectives for fintech competition.

From a policy perspective, a regulatory-driven innovation approach to open banking shows that technology neutrality is essential in developing regulation on financial innovation that considers data privacy and consumer protection. Open banking initiatives encompass diverse objectives, with typical themes revolving around promoting innovation, encouraging competition, and empowering customers through increased choice, evident in both current and prospective frameworks. In this context, innovation entails developing novel products and services within the banking and payments sector and beyond. Promoting innovation can positively impact competition dynamics in financial services, resulting in more efficient and cost-effective services that enhance the overall customer experience. Customers now have control over their financial data and choose what data to share under data access and sharing agreements, making client empowerment a top priority. However, this effect of open banking is underlined. Main regulatory challenges are still open, starting from harmonising frameworks to improve cross-country and sector interoperability, common security standards, standardisation of API, data ownership, and remuneration. Substantial work remains on this evolutionary trajectory of financial innovation, where the centrality of data remains paramount (OECD, 2023).

A comprehensive understanding of the current state of open banking frameworks is essential for shaping future open finance policies aimed at unlocking the intrinsic value of data. Extending data-sharing policies horizontally across all financial intermediary sectors outside banking introduces heightened complexity in designing future frameworks. Simultaneously, enforcing these frameworks should adopt a modular approach, respecting the specificities of vertical sectors. Collaborative efforts among regulators become imperative to establish a cohesive data-sharing policy for the financial sector. Future studies should delve into the welfare implications of open banking across various loan types, assess the effects of cross-country interoperability, scrutinize the mechanisms underpinning data-sharing remuneration, and explore the dynamics of collaboration through open banking involving TradFin, BigTech, and FinTech entities. In a broader context, the impact of developing open finance frameworks that extend data-sharing across financial sectors represents a fundamental step in driving financial innovation.

3. From Blockchain to DeFi and CDBCs

3.1. Blockchain

This section focuses on the theoretical and limited empirical literature on blockchain, discussing their main implication and limitations behind the adoption of distributed larger technology as fundamental background for the policy considerations that are presented in the upcoming section on DeFi and CBCDs. The literature review provides an overview of the functioning of blockchain and an exploration of the fundamental economic functions in conjunction with the protocol mechanisms. The initial paragraph delves into the characteristics of proof-of-work (PoW) and its constraints within the context of the Bitcoin technology architecture, economics and governance (Böhme et al., 2015). Subsequently, it examines the crucial distinctions inherent in proof-of-stake (PoS). Moreover, this section presents preliminary empirical findings about cryptocurrency volatility and interconnectivity.

Before getting into the actual literature, it is fundamental to define some basic concepts behind Bitcoin and blockchain to understand the context of the discussion. A blockchain is a digital ledger that records transactions in blocks. These blocks are then linked sequentially and unchangeable to form an immutable chain known as "blockchain". Generating and accepting new blocks into the blockchain is crucial to maintain the integrity and security of the network. In the case of Bitcoin, a consensus protocol called Proof of Work (PoW) is used to validate and add a block to the blockchain. PoW creates a computational problem for each chain of blocks and the solution to this problem is used to validate the block. This process is known as mining, where participants called miners compete to solve the computational puzzle. Mining ensures security and facilitates the processing of transactions in a decentralized manner, making blockchain a reliable and trustworthy technology (Nakamoto, 2008). The Bitcoin underlying technology was to create a decentralized payment system that any central authority could not control, and at the same time, eliminate the issue of double-spending. The double-spending problem refers to the risk of a user spending the same Bitcoins twice, which can compromise the security of the payment system. To overcome this problem, Bitcoin uses a combination of cryptographic algorithms and a distributed ledger system to ensure that the probability of a successful double-spend is reduced to an extremely low level. The Bitcoin design limits the number of transactions included in each block, leading to a capacity constraint. As a result, miners need to prioritize transactions based on the fees offered by users. This means that those who offer higher fees are likely to have their transactions confirmed faster than those who offer lower fees. To avoid long wait times, users must balance the cost of paying higher fees against the benefit of a faster transaction.

The theoretical literature has studied this dynamic results in the endogenous determination of an optimal fee, which reflects the trade-off between transaction speed and cost. This mechanism has emphasized the importance of fee optimization in the Bitcoin ecosystem (Easley et al., 2019). The primary advantage of a blockchain lies in expedited and adaptable settlement processes. However, the risk of settlement failures arises when participants bifurcate the chain to nullify trading losses. In the context of a PoW protocol, the blockchain must curtail settlement speed by regulating block size and time to generate transaction fees, which, in turn, fund resource-intensive mining activities

(Chiu and Koeppl, 2019). Blockchain transaction fees are an essential aspect of the blockchain ecosystem, serving as compensation for the miners who participate in the costly process of extending the blockchain with new entries. While mining rewards may initially come in the form of new cryptocurrency tokens, these rewards decrease over time in many popular blockchains, including Bitcoin. As a result, congestion-induced transaction fees will eventually become the primary source of mining rewards. However, users may exit the blockchain instead of paying enough fees to compensate miners for their investment in reliable mining infrastructure (Sokolov, 2021). Another work has examined how Bitcoin users interact with the economic payment function and miners. The study highlights the importance of limiting the scale of a decentralized system to maintain its security against attacks and determining the exchange rate and volatility of the coin (Huberman et al., 2021). Bitcoin was conceived to serve as an extensively embraced decentralized payment system. The challenge of scalability, however, still needs to be solved, as escalating transaction rates amplify the likelihood of forks. This outcome extends the consensus process and restricts adoption, thereby hindering the envisioned widespread acceptance of Bitcoin (Hinzen et al., 2022).

This structural limitation of PoW has been partially overcome by a different consensus mechanism that hopes to create a sustainable permissionless blockchain. PoS diverges from PoW competitive structure by endowing a randomly selected stakeholder responsible for updating the blockchain. In doing so, PoS eliminates the incentive for validators to engage in a computational arms race. Nevertheless, scepticism persists regarding the long-term viability of PoS as concerns arise about its ability to foster consensus. While both PoS and PoW offer validators a tangible monetary reward, known as a block reward, for updating the blockchain, PoS, unlike PoW, does not necessitate validators to incur an explicit monetary cost, such as solving PoW puzzles, to acquire the authority to update the blockchain. A step forward in the literature has proposed two different design approaches to developing PoS consensus within the blockchain. The first approach involves a minimum stake threshold, limiting the validators who can update the blockchain to those with a certain minimum amount of native coins. The second approach allows developers to implement a block reward schedule, which refers to the number of native coins given to a validator for updating the blockchain with a new block (Saleh, 2021; Roşu, and Saleh, 2020; Amoussou-Guenou, 2023). An important aspect related to the consensus mechanisms of blockchain technology is its governance. According to Ferreira et al. (2022), Nakamoto's original vision of blockchain governance is not feasible. This is because corporate capture is inherent in PoWs' design, as market power spreads through the mining ecosystem. If a large company controls the blockchain's governance, stakeholders must rely on that single company to protect their interests. This begs the question of how a permissionless blockchain differs from a traditional financial institution that provides trusted services. However, blockchains' governance structure about the consensus mechanism is still an important area unexplored.

Moving forward from this theoretical foundation, important insights come from the empirical literature that has studied the implication behind consensus mechanisms and their reflection on the price and volatility of cryptocurrencies. This literature has used empirical methodology from the financial market, asset pricing, and IPO studies to analyse the cryptocurrency market. Seminal research has investigated the price dynamics of the cryptocurrency market, revealing arbitrage opportunities across exchanges that often persist for several days and weeks. This indicates significant market segmentation, with the arbitrage spreads being much larger for exchanges across different countries than within the same country. Interestingly, exchange rates between different cryptocurrencies show much smaller deviations on all exchanges. primary. This evidence underlines the lack of regulatory oversight on crypto exchanges is the main factor contributing to market segmentation (Makarov and Schoar, 2020). Additionally, works have demonstrated a strong correlation between cryptocurrency returns and the underlying network factors of the cryptocurrency market, as predicted by the theoretical literature. Furthermore, two market-specific factors, namely momentum and investor attention, have been identified as predictors of cryptocurrency returns. These two factors are independent phenomena that have limited interaction. At the same time, cryptocurrency returns have low exposure to macroeconomic factors compared to traditional asset classes such as currencies, commodities, and stocks. This evidence is also considered in the three facto models that consider the cryptocurrency market, size, and momentum (Liu et al., 2021; Liu et al., 2022). This initial literature and evidence from the empirical analysis highlight the fragility of the cryptocurrency market and the need for an effective regulatory and supervisory framework that is extensively discussed in the next section in relation to also DeFi applications.

3.2. Decentralized Finance

This section takes a step further from the previous, focusing on more technical aspects of blockchain distributed ledger technology in discussing smart contracts and decentralized finance (DeFi). In detail, this part of the literature illustrates first the basic concept and definition of smart contracts and stablecoin in relation to different DeFi applications such as token issuance, nonfungible tokens, decentralized exchanges, and protocols for loanable funds that present the upcoming regulation in relation of crypto assets and main supervisory challenges.

In order to better understand DeFi, it is crucial to start with a clear definition of smart contracts. Fundamentally, a smart contract is a computational code deployed onto a blockchain, embodying two primary constituents: state variables and functions. The confluence of state variables collectively constitutes the smart contracts' state, while functions operate as mechanisms facilitating transitions from one state to another. Within the blockchain, all transactions unfold as a sequential progression of state transitions, wherein the blockchain state encapsulates the comprehensive array of states across all smart contracts on the blockchain. In order to enable Blockchain payment functionality, it is essential to have token smart contracts that include a state variable to keep track of the token holdings of each user. This way, any payment made can be considered as a change in the distribution of these holdings. To achieve this, a token transfer function is implemented within the contract, which modifies the state variable responsible for storing the token holdings of each user. By doing so, token transfers can seamlessly take place between users, allowing for a secure and efficient payment system. Furthermore, to embrace the payment system functionality of the blockchain, several projects have started creating stablecoin to minimize the volatility of cryptocurrencies and stabilize the underlying value of the token. Stablecoins are a type of cryptocurrency that are designed to maintain a steady value relative to a specific asset or a group of assets (FSB, 2020). Unlike traditional account-based payment systems, stablecoins use token-based verification, where the validity of tokens is determined by the tokens themselves rather than the parties' identity. To distinguish them from fiat currencies, policymakers often refer to cryptocurrencies as "crypto-assets," highlighting their nature as an asset class rather than a currency. The academic literature has started studying smart contracts and how decentralized ledger technologies can facilitate the creation of smart contracts and blockchain applications. From a micro perspective, the process of reaching a decentralized consensus through blockchain technology has the potential to change the information environment in various ways. On one hand, it can facilitate enhanced entry and competition, leading to higher social welfare and consumer surplus. On the other hand, it may also promote collusion among participants, which can result in welfare-destroying consequences. While blockchain and smart contracts can help sustain market equilibrium with a wider range of economic outcomes, the need for regulatory and market solutions cannot be ignored (Cong and He, 2019). An additional contribution comes from Cong et al., 2021 who have studied the interconnectedness of token pricing and platform adoption within a dynamic equilibrium framework. The authors posit that platforms generate value by facilitating specific economic activities, and correspondingly, the value of platform tokens is contingent upon their role in enabling transactions among a diverse user base. The valuation of tokens is asserted to be intricately linked to user participation and the consequential network externality effects. The more users engage with the platform, the greater the value attributed to the token. Furthermore, the paper posits that the endogenous nature of the user base significantly contributes to explaining cross-sectional variations in token pricing, the dynamic nature of token price volatility, and the phenomena of token prices experiencing ascents and descents. This discussion has been reflected in the optimal design of the blockchain. The consensus mechanism inherent in the platform poses a challenge that eludes facile resolution through conventional frameworks governing the allocation of control and cash flow rights. Firstly, tokens exhibit less efficacy than equity in extracting value from a platform. This inefficiency stems from the reliance of token prices on the convenience yield of the marginal user, contrasting with equity, which derives its valuation from the average user and the platforms' revenue generated from transaction fees. Secondly, although individual users are disinclined to act against their self-interests by undermining the platform, they lack the individual incentive to subsidize their participation in the platform despite its societal optimality. Lastly, the endowment of tokens with cash flow and control rights introduces the prospect of users or external entities accumulating tokens to centralize the platform. This potential concentration of tokens reintroduces the commitment problem, particularly when token prices are low and the platform becomes susceptible to subversion (Sockin and Xiong, 2023; Cong et al., 2022). An important advancement in this literature comes from an empirical study made by Griffin and Shams in 2020, which focuses on the interplay between blockchain, Bitcoin, and one of the prominent stablecoin blockchains. The study reveals the complex interconnectedness among cryptocurrencies and highlights the vulnerability of cryptocurrency exchanges. The results demonstrate that stablecoins show a timed response to market downturns, leading to significant increases in Bitcoin prices. This flow can be attributed to a single entity, resulting in clusters of transactions occurring below round prices. Additionally, this phenomenon induces asymmetric auto-correlations in Bitcoin, indicating a nuanced relationship between the two currencies.

The fragility related to cryptocurrency interconnectedness discussed in the literature has shown its potential effect in the recent downturn in the Terra-Luna ecosystem in May 2022, along with other crises such as the recent collapse of FTX, a significant crypto operator valued at $32 billion, indicates the urgent need for clear regulatory guidelines. Such guidelines would define rules for operators and ensure the protection of users. The roles of various authorities involved and the forms of collaboration required should also be clearly defined, considering the cross-border nature of these markets (Arner et al., 2020). An important step forward in this direction has been the European Commission with the approval of Markets in crypto-assets regulation (MICAR) that gives a clear legal definition of crypto-assets referring to stablecoins as asset-referenced tokens or E-money tokens and Crypto-Assets Service Providers and issuers.[1] Regulators and supervisors are facing difficulties in monitoring crypto-assets and associated activities. There are risks not only for security tokens or stablecoins but also for entities issuing utility tokens, governance tokens, or non-fungible tokens. However, regulators and supervisors continue to face challenges in monitoring crypto-assets and associated activities. There are risks for security tokens or stablecoins and entities issuing utility tokens, governance tokens, or non-fungible tokens. There are no specific regulatory frameworks for these tokens at present. In the future, regulatory bodies may consider imposing restrictions or specific criteria for using utility tokens as investment instruments. Additionally, national competent authorities (NCAs) may need to evaluate whether adjustments to the regulatory scope are necessary to include emerging participants engaged in services provided via DeFi applications, which are not regulated. Crypto-asset service providers assume diverse roles encompassing transaction facilitation, settlement and clearing, wallet provisioning, market-making, investment offerings, lending and borrowing, and proprietary trading and issuance. Certain jurisdictions may restrict specific combinations of services, necessitating comprehensive regulation, supervision, and oversight where permissible. Such oversight should incorporate robust safeguards for investors and consumers. Must consider requirements addressing risks in isolation and additional risks and conflicts arising from concurrent activities. Cross-border and cross-sectoral

[1] Asset-referenced token: maintains a stable value by referring to several fiat currencies, one or several commodities or one or several crypto-assets or a combination of such assets. E-money token: maintains a stable value by referring to the value of one fiat currency

information sharing regarding service providers operating across diverse jurisdictions and sectors is imperative. Collaborative information exchange aims to prevent financial distress from permeating other jurisdictions or sectors within the financial system (Ocampo et at., 2023; FSB, 2023).

In addition, academic research is crucial for answering fundamental questions that are still open, such as the exposure of the banking system to the crypto-asset market, the interdependence between crypto-asset and centralized and decentralized exchanges, and the theoretical implications of the applications of DeFi.

3.3. Central Bank Digital Currencies

The following section delves into the recent research and development initiatives focused on central bank digital currencies (CBDCs). This part differs from the previous paragraphs and focuses on the use of distributed ledger technology in central bank analysis of fundamental design challenges and policy implications. This part of the literature presents some seminal works on microeconomic considerations related to operation architectures, technologies, and privacy in detail, as well as the macroeconomic implications for the financial system, financial stability, and monetary policy. When considering the adoption of CBDCs, the first aspect to be considered is the operational architecture. One possible solution is to involve the private sector to avoid overburdening the central bank in relation to the payment function of distributed ledger technology. Another option is to have the private sector conduct all retail payments while the central bank operates a backup infrastructure. This hybrid CBDC architecture combines the credibility of a direct claim on the central bank with the convenience of private sector payment services. However, it is important to note that while most central bank CBDC research and development projects involve a hybrid or intermediated architecture, many academic studies still describe CBDCs as if the central bank were taking on all operational tasks, without any role for private intermediaries (Auer et al., 2022). There are still several important issues that need to be addressed regarding the design and adoption of CBDCs. These include determining the best technology to support the operational architecture, ensuring data privacy during payment transactions, and enabling cross-border interoperability between multiple CBDCs. The academic literature has begun to explore some of these critical aspects from a microeconomic perspective. Agur et al., 2023 analysed the optimal design of a CBDC in an environment where individuals prefer cash, CBDCs, and bank deposits based on their preferences for anonymity and security. The study found that the optimal CBDC design involves balancing bank intermediation with the social value of maintaining diverse payment methods. It highlights important policy trade-offs when they compete with cash and bank deposits. When a digital currency offers benefits that cash does not, there is a tough choice between promoting financial inclusion and enabling illicit activities. Similarly, if a CBDC competes with bank deposits, there is a tension between facilitating efficient exchange and investment. The central bank can navigate these trade-offs by creating specialized CBDCs for specific purposes, which allows them to set appropriate interest rates and other design features. However, if a digital currency is universal, the central bank must carefully weigh both trade-offs in its design (Keister and Sanches, 2023). Furthermore, research has examined the design of CBDCs and their potential impact on adoption, focusing on the effects on monetary policy and financial stability. The distributed ledger technology's payment functionality is not restricted to retail. Rather, it can be extended to the existing clearing and settlement platform for interbank payments, thus enhancing the efficiency of the underlying systems (Williamson, 2022). However, CBDCs could weaken smaller banks without access to large funding markets. A crucial aspect of financial stability is the possibility of introducing deposits in CBDC. This implication on deposits in CBDC accounts can decrease the supply of private credit by commercial banks, which increases the nominal interest rate and subsequently lowers a commercial bank’s reserve-deposit ratio. This can negatively affect financial stability by increasing the likelihood of bank panic, which causes commercial banks to have insufficient cash reserves to pay depositors. However, once the central bank lends all the deposits in the CBDC account to commercial banks, an increase in the quantity of CBDC, which does not require reserve holdings, can enhance financial stability by increasing the supply of private credit and lowering the nominal interest rate. This positively affects borrowers, which tends to dominate the negative effect on depositors or lenders, except for a sufficiently large quantity of CBDC. At the same time, CBDCs provide a secure option for commercial bank deposits, which can be especially relevant when commercial bank deposits exceed the insurance limit and pose potential risks. In times of crisis, CBDC can encourage deposit holders to move their funds from the commercial banking system to CBDC, introducing the possibility of a systemic run instead of just a run on a single bank. It is important to note that the risk is not only limited to a single bank run but also extends to a higher risk of a systemic bank run. This is because households can initiate a run on an individual bank by transferring their deposits to a perceived safer institution while still keeping their funds within the broader banking system, regardless of the presence of CBDC. Although the introduction of CBDC does not change the dynamics of this type of run, it may increase the likelihood of a systemic banking run (Fernández-Villaverde et al., 2021; Williamson, 2022). Cross-border payments are expensive, slow, lack transparency, and are not accessible to everyone. However, with CBDCs, it may be possible to create arrangements allowing more banks and non-banks to access central bank money for payment settlements. This could lead to more diverse cross-border payment services, making cross-border payments more inclusive and accessible to a broader range of people (Auer et al., 2022).

In the end, the emerging literature and discussion on the possible design and adoption of CBDCs raise several questions that still need to be addressed. These include the compatibility between existing and new infrastructures, control over and access to central bank funds, the difference between wholesale and retail CBDCs, and the cross-border implications of CBDCs. Another important aspect is deciding whether to implement token-based or account-based CBDCs and how to authenticate accounts within the "know your customer" process. Technical issues also need to be considered within the political dimension of CBDC adoption, including the need for public funding and resources to continue developing pilot projects to solve the technical challenges. The impact and welfare implications of CBDCs would vary depending on the maturity of the financial infrastructure where they are introduced, reflecting the jurisdiction policy objects. Developed countries such as the US and EU, which already possess efficient payment infrastructures, would have a different experience than developing countries, where CBDCs could significantly impact financial inclusion by improving their settlement systems. Ultimately, academic literature and research continue to play a vital role in analysing the possible impact of CBDCs within theoretical modelling and future empirical research when some data is available.

4. Cybersecurity Risk

The financial sector has become increasingly vulnerable to cybersecurity risk due to the growth of data availability and the adoption of technology-based financial products. The cybersecurity risk has been naturally embedded in all digital products product to the market, increasing exponentially the interception between customers and providers and, more importantly, over the production supply chain. This new source of risk has highlighted how the evolution of financial innovation can threaten financial stability and customer protection. Cybersecurity risk can generate exogenous shocks, generating and amplifying traditional sources of financial risk such as liquidity, operational, reputational, outsourcing, concentration risk, and systemic risk. Indeed, cybersecurity has become a priority for regulators and supervisors within the scope of mandate to maintain financial stability and market integrity.

The limited and recent development literature on cybersecurity risk has analysed it as a cross-sector phenomenon with some specific focus on the financial sector concerning the impact of possible additional threats to financial stability and resilience. This literature funded a solid theoretical foundation in the works that have studied idiosyncratic shock propagation through network effects (Barrot and Sauvagnat, 2016; Costello, 2020; Elliot et al., 2022). The propagation effect of cyber-attacks can be compared to natural disasters and credit supply shocks. Just like external shocks, the impact of cyber-attacks can devastate suppliers, resulting in significant output losses that can spill over to their customers and other suppliers in the market. These losses can be particularly severe when suppliers produce precise inputs to a particular industry. This network dynamics highlights the importance of input specificity as a critical factor in the propagation of idiosyncratic shocks throughout the economy (Barrot and Sauvagnat, 2016). Moreover, there might be an indirect effect of this interdependence between production networks, and the liquidity spillover effect may aid in explaining the magnitude and persistence of the corporate slump (Costello, 2020). This implication on the overall structure of the supply chain networks has underlined the risk of idiosyncratic failure, which threatens to disrupt production and have systemic importance and relevance (Elliott et al., 2022).

The literature on cybersecurity initially examines the key factors driving this emerging threat, highlighting the elevated cyber-related expenses faced by businesses at risk of contagion effects. These costs can be mitigated through investments in technology and IT infrastructure enhancements (Aldasoro et al., 2022). Nevertheless, this initial analysis must consider the broader implications of systemic failures concerning cyber resilience in critical industry sectors. However, additional evidence has shown the impact of reputation costs due to cyber-attacks. The effects of such attacks can have a significant impact on a company's shareholder wealth. This impact can be even larger than the out-of-pocket costs incurred due to the attack (Kamiya et al., 2021). Indeed, firms that mitigate the effects of additional cyber-attacks in moments of vulnerability after having experienced a cybersecurity attack significantly increase cash holdings, reducing the possible additional progradation effects of the liquidity shock (Garg, 2020). The impact of a cyberattack on firms can be quite severe, as it can lead to a four-fold amplification of the initial drop in profits due to the fragility and interconnection of the supply chain. However, firms with internal liquidity buffers and increased reliance on borrowing, primarily through bank credit lines, are better positioned to withstand such attacks. Even then, the aftermath of a cyberattack can lead to enduring adjustments in the supply chain network. For instance, affected customers may choose to terminate their existing trading relationships with the directly impacted firms and establish new ties with alternative suppliers who are known for their superior cybersecurity measures (Crosignani et al., 2023). Florackis et al., 2023 made a step forward in the literature by creating a novel measure of cybersecurity risk to price in the cross-section of firms' stock returns. Analysis of the correlation with several characteristics linked to firms hit by cyberattacks, such as size, age, growth opportunities, asset tangibility, cybersecurity risk expenditures, and trade secrets, shows that cybersecurity risk is incorporated within the stock returns in financial markets. On the other hand, a limited number of studies have focused their attention on the impact of cybersecurity on financial systems, studying the crucial role of the payment system in disseminating the effects of cyber-attacks on a single large bank, a group of smaller banks, or a common service provider. In particular, cyber-attacks that block the payment infrastructure can significantly amplify the effect of liquidity shock, posing a potential threat to financial stability. Moreover, if there is uncertainty regarding the attack, banks are likely to respond strategically, which can further exacerbate the amplification effect (Eisenbech et al., 2022).

Cybersecurity risk has recently become a top priority for regulators and supervisors. With the rapid digitalization of the financial sector and the ongoing geopolitical crisis, the vulnerability of financial systems is increasingly evident. The adoption of regulatory frameworks to mitigate potential ripple effects and contagion dynamics to improve cyber resilience should consider microprudential and macroprudential principles and the fact that most of the critical cloud infrastructure from few BigTech (Doerr et al., 2022; Kashyap and Wetherilt, 2019). These elements should be ground into regulatory body and supervision practices. On the one hand, from a microprudential perspective, firms need to take into account the potential impact of systemic risks. To do so, they should operate under the assumption that a high-impact attack is inevitable. This means that firms need to develop a plan for dealing with prolonged and system-wide disruptions, focusing on allocating resources for response and recovery. This means that firms need to develop a plan for dealing with prolonged and system-wide disruptions, focusing on allocating resources for response and recovery (Kashyap and Wetherilt, 2019). On the other hand, from a macroprudential point of view, it is crucial to plan for system-wide disruption by setting appropriate recovery expectations to deliver critical economic functions. One way to achieve this is by conducting cyber stress tests that explore common vulnerabilities that may amplify the impact of a cyber shock. These tests help identify potential vulnerabilities and encourage firms to make more diverse infrastructure or software choices to avoid common vulnerabilities. Ultimately, the goal is to ensure that critical economic functions are not affected during a cyber-attack (Kashyap and Wetherilt, 2019). Part of this high-level principle will be introduced by the Digital Operational Resilience Act at the European level, considering also the BigTech functional in providing critical cloud infrastructure based on proportional principles and with a horizontal approach to the sector. Furthermore, the push of central banks on CBDCs has also increased the budget for cybersecurity within the design of new financial systems infrastructure (Doerr et al., 2022). However, this initial consideration on cybersecurity needs for future development, especially looking at the enforcement of the regulatory frameworks, the adoption of common standards at the global level, and defined supervisory practices to mitigate cyber risk threats. Indeed, adopting cybersecurity risk frameworks could also create additional barriers to financial innovation by imposing supplementary operating requirements in providing financial products via digital channels.

Academic literature should continue to develop distinctive ways to detect the impact of cybersecurity risks and estimate their potential effects. Policymakers and the literature could benefit significantly from examining the interplay between cybersecurity risks and traditional financial risks to understand how these non-financial sources of risk could lead to financial instability and market integrity issues. Specifically, one area that requires fundamental development for research is the role of cybersecurity in payments infrastructure, as well as the relation with the potential introduction of CBDCs.

5. SupTech: a banking supervision perspective

The previous sections have discussed the impact and risks associated with the current change in financial innovation due to the adoption of emerging technologies. From a regulatory standpoint, much has been done to address the non-financial and financial aspects of the digital transformation of financial systems. At the same time, supervisors have slowly adopted the same technology to improve their practices. The application of emerging technology for supporting supervisory practices is broadly called SupTech. Technology neutrality allows supervisors to leverage the same data-driven applications used by the market to design supervisory tools. Indeed, the idea behind SupTech is to use the same data and information that the market generated to improve microprudential and macroprudential activities (Di Castri et al., 2019). This technology is transforming the practices of supervisors and has brought into question the organisational structure of their authority and the underlying architecture. The challenges brought about by SupTech are similar to those faced by TradFin with the rise of FinTech and BigTech. Supervisors should follow the same technological trends as the market to have tools to maintain financial stability and integrity. This section discusses the interplay between the policy implications of SupTech development and the literature on banking supervision, underlining some of the implications and challenges behind the use and adoption of emerging technology on supervision. This pushes forward the discussion on financial innovation, including the supervision perspective, leading to more fundamental questions about the role of data-driven technologies for supervision: How is technology changing supervisory practices? How will the coding of soft information into hard information change the supervisory architecture and organization structure? How will SupTech impact banks' risk-taking and performance?

Starting from a micro perspective, how the organisation has been structured to acquire information corresponding to activities in deterring efficient processes and measuring the performance outcomes has been discussed (Aghion and Tirole, 1997). Within the context of supervision, NCAs based their activities on analysing and processing data into information to identify possible threats to financial stability and market integrity. Supervisors have started leveraging the same emerging technologies to improve the efficacies of their internal process in microprudential and macroprudential activities in the area such as customer protection, anti-money laundering, cyber risk supervision, securities supervision, payment oversight, digital assets and cryptocurrency, licensing, ESG risk supervision, etc. (Di Castri et al., 2022). On the other hand, the literature on banking supervision has shown that bank on-site inspections are crucial to collecting information and mitigating risks during financial distress (Hirtle and Lopez, 1999). Furthermore, the strangeness of bank supervision due to enforcement action and direct on-site inspections reduces banks' fragility and risk exposure (Bassett et al., 2015). This relationship suggests that enforcement actions indeed wield a disciplinary influence over banks. Additionally, the inverted U-shaped correlation between on-site audits and banking fragility is U-shaped, indicating that increasing the frequency of examinations can limit bank risk up to a certain point. Similarly, there is a negative correlation between disclosure requirements and bank risk. These insights highlight the importance of effective bank supervision in maintaining a stable and secure financial system (Delis and Staikouras, 2011). The study reveals that enforcement actions taken against banks can positively impact their financial stability. It shows that such actions significantly reduce both the risk-weighted assets and the nonperforming loan ratios of the punished banks. While there is no observed increase in the level of regulatory capital, the results suggest that enforcement actions can go a long way in improving the overall health of banks. These findings are encouraging, and they underscore the importance of a strong regulatory framework that can help ensure the banking sector's stability (Delis et al., 2017; Deli et al., 2019). This first part of the literature has highlighted the effect of supervision on banks' risk-taking. However, the NCAs face structural constating in terms of internal capability and resources that could limit the positive effects of supervisors (Crisanto et al., 2022). To better understand the mechanisms of the implication on bank supervision, other research has used the total number of hours spent on supervision as the measure to explore the impact on bank performance and outcomes, showing how bank size is the factor that catalyses the attention of prudential authorities mitigating banks' risk-taking (Hirtle et al., 2020; Kandrac and Schlusche, 2021). Eisenbach et al. (2022) have introduced the element of technology in banking supervision, pointing out that larger banks are easier to monitor through economies of scale into supervisory technology. Still, this emerging stream of research needs to consider how emerging technology is changing supervisors' activity and architecture. Indeed, the centralized supervisory architecture that relies on authority to establish rules but delegates monitoring and enforcement responsibilities to local supervisors, known as "hub-and-spokes," can lead to potential agent problems and inefficiencies in the information collection process due to differences in the objectives of various supervisors involved. The collation of soft information has become crucial for building efficient bank regulatory frameworks through aligned supervisors' objectives across layers of competence (Gopalan et al., 2021; Carletti et al., 2021). This is the case with the single supervisory mechanism (SSM), where bank supervision is conducted on two levels (Fiordelisi et al., 2017). The same clarity on supervisors' objectives and standards should drive the process of adopting SupTech applications and the information collection across levels of competence, reflecting the data architecture into the supervisory ones. The impact of SupTech on banks' performance and risk-taking is still unexplored. Understanding the effect of the redefinition of supervisors' practices based on information flows could contribute to explaining the market response to future microprudential and macroprudential policies. The high heterogeneity in the sizes of NCAs and their resources can create significant gaps in the adoption and development of SupTech, creating a need for cross-border collaboration. Indeed, this type of cooperation arrangement among countries is essential to benefits and costs predicted by externalities and heterogeneity across countries to acquire higher quality information to improve supervisors' infrastructure (Beck et al., 2023). On the one hand, NCAs face the same day-to-day supervisory challenges in automating and improving their capabilities and practices. On the other hand, supervisory and regulatory architecture has a hub and spoke structure, which needs to be replaced to develop and adopt SupTech. (Carletti et al., 2021; Gopalan et al., 2021). It would be essential to define tech hubs inside the current supervisory architecture. They should be capable of designing and creating blueprint SupTech solutions that NCAs could plan to reduce the technologies' cost and generate economies of scale (Eisenbach et al., 2022).

The digitization of supervision is an ongoing process that can significantly contribute to the policy debate on the impact of SupTech on the market. However, identifying the adoption of SupTech technology and defining alternative measures for supervisors' efficiency still pose empirical challenges. Future works should focus on collecting additional and innovative data sources in collaboration with NCAs to study the effects of emerging technologies on banking supervision. This should be done within the current understanding of supervisory architecture, including the drivers and mechanisms for scaling up the adoption of SupTech.

6. Conclusion and policy implication

This paper has bridged academic research and policy discussion to analyse the most recent development in financial intermediation literature in digital finance. This different approach contributes to literature by giving a policy dimension to academic works. Furthermore, the papers explore potential areas for future research that could bridge the gap between policy analysis and academic research, thus significantly influencing the ongoing policy discussions. From an academic perspective, some of the open research questions that still need to be investigated include the welfare implication behind technology-based lending and data-sharing policies, the identification of the banks' expense to crypto-asset, the measuring of cybersecurity risk and the possible impact of systemic risk and the implication of the use of technology in financial supervision concerning the risk-taking of the market. However, this future development of the literature should be based on the use of property and supervisory data to conduct research. At the same time, the challenges faced by supervisors and regulators remain ongoing within the rhythm of the evolution of digital finance. On the one hand, supervisors are trying to keep up with the speed of financial innovation by adopting and using the same technologies that are changing how financial services are provided to improve their capabilities. On the other one, regulators are changing how they approach regulatory frameworks that aim to take care of novel sources of risk and facilitate financial innovation, re-discussing their regulatory perimeters. In both cases, digital finance has underlined the crucial need for regulatory and supervisory collaboration to go behind the national barriers in designing regulatory frameworks based on common principles and supervisory technologies that go beyond borders. In the end, the real future challenge for regulatory and supervisory is to establish cross-border collaborations that are capable of reflecting the international dimension of digital finance.

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Appendix 1

The table below presents the top 20 academic journals according to the Central Bank ranking. The ranking was conducted during three periods: 2007-2016, 2013-2022, and 2014-2023. This ranking was used for the literature review based on the work from Auer et al. (2023).

	Central bank citation rank		
Journal name	2007–16	2013-22	2014-23
Brookings Papers on Economic Activity	7	2	1
The Quarterly Journal of Economics	2	1	2
Journal of Monetary Economics	3	3	3
American Economic Journal: Macroeconomics	10	5	4
Journal of Political Economy	1	4	5
American Economic Review	16	6	6
Journal of Economic Literature	5	9	7
International Journal of Central Banking	12	8	8
Review of Economic Studies	6	7	9
Journal of International Economics	9	10	10
The Review of Economics and Statistics	13	13	11
Journal of Finance	11	12	12
Journal of Money, Credit and Banking	8	11	13
Review of Economic Dynamics	14	14	14
Journal of Economic Perspectives	19	16	15
IMF Economic Review	29	15	16
NBER Macroeconomics Annual	31	20	17
Journal of Financial Intermediation	22	17	18
Journal of Economic Growth	23	19	19
Review of Financial Studies	25	18	20
Econometrica	4	22	21
Journal of the European Economic Association	15	41	40
Journal of Business & Economic Statistics	17	39	44
Journal of Applied Econometrics	18	24	24
International Economic Review	20	66	61

Does regulatory-driven innovation affect traditional financial intermediaries? Evidence from open banking frameworks.

Nico Lauridsen*

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Abstract

This paper examines the mechanisms underlying the policy implications of open banking frameworks. The data-sharing policy in financial intermediaries aims to alleviate friction in information asymmetry and promote financial innovation by enhancing market competition and data portability. This study uses a difference in differences approach to explore the impact of adopting open banking on traditional financial intermediaries in the European syndicated loan market. The results reveal a discrepancy across the policy intervention phases. Specifically, the introduction of open banking frameworks leads to a significant reduction in loan interest rates without affecting collateral. However, the regulatory fragmentation in enforcing data-sharing policies and the specific characteristics of syndicated loans limit the positive effects of data portability and interoperability competition. This finding underscores the crucial role of regulators in establishing financial innovation policies and emphasises how private information continues to play a significant role in the syndicated structure.

Keywords: open banking, financial innovation, data access, syndicated loan, policy intervention.

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1. Introduction

This paper studies the implications of adopting open banking frameworks in the credit market to explore the mechanisms behind regulatory-driven innovations and provides empirical evidence of the impact of data-sharing policy on traditional financial intermediaries (TradFis). In the past two decades, an exponential increase in data availability and portability has facilitated the development and adoption of emerging technologies such as artificial intelligence, machine learning and blockchain, redefining how financial services are provided. This technological development in the capacity to process data has imposed a radical change on financial intermediaries and market dynamics. Therefore, digitalised data into information has become a fundamental asset for financial intermediaries that drives market efficiency in financial innovation (Veldkamp, 2023). However, the rise of the data economy in the financial system also comes with consequent risks from novel business models designed to exploit technology. This emerging risk related to the technology involved in financial innovation adds to the traditional risk associated with financial intermediation, amplifying and increasing possible financial instability and market integrity threats (Aldasoro et al., 2022). At the same time, this should be balanced with policy to facilitate financial innovation via market competition. However, the exponential use of data leads to regulatory challenges that go beyond the traditional trade-off between market competition and financial stability (Feyen et al., 2021). Indeed, the design of financial innovation regulatory frameworks should break this dichotomous relationship and include data privacy and customer protection as a third missing dimension that is crucial and affects financial stability and market integrity (Chen et al., 2021). On the one hand, data availability and portability has become one of the main drivers of efficiency and competition in the financial innovation market. On the other hand, the cyber risk component that is embedded in the digitisation process and possible data manipulation or algorithmic abuse could threaten financial stability and integrity (Crosignani et al., 2023; Fuster et al., 2022; Chen et al., 2023). In this policy puzzle regulatory interventions have tried to combine these three dimensions of facilitated financial innovation, which remains a crucial endogenous force for economic growth (Leaven et al., 2015). Open banking frameworks aim to combine these policy objectives to promote financial innovation by increasing market competition and data availability and improving customer protection, underlining how crucial it can be as a policy intervention in fostering evolution of the financial sector. What can be learned from the open banking experience is that it is essential to understand how regulatory intervention can drive financial innovation.

Globally, more than 80 jurisdictions have promoted various open banking initiatives as data-sharing policies to facilitate secure access to and use of payment data to support the development of the so-called fintech market (Babina et al., 2024). However, the real impact of open banking frameworks on financial intermediaries still needs to be studied. The theoretical literature on open banking describes how payment data competition helps improve lending quality by reducing information asymmetry between borrowers and increasing market efficiency, but with an ambiguous consumer welfare effect (Parlour et al., 2022; He et al., 2023). At the same time, empirical research on the use of emerging technology in the activities of financial intermediaries has been limited to digital and fintech lending applications (Fuster et al., 2021; Fuster et al., 2022; Di Maggio & Yao, 2021; Berg et al., 2020). This paper goes a step forward by asking a fundamental question about the other part of the story: do data-sharing policy interventions affect access to credit by traditional financial intermediaries?

The open banking framework is a two-sided market in which the definition of standards and rules on data-sharing involve TradFis and fintech. From the TradFis perspective, open banking frameworks are not limited to sharing payment data with third parties but they also leverage overall interpretability among the same players. Indeed, data-sharing policies become effective when both sides of the model get benefits from the intervention. This study contributes to the literature by giving empirical evidence on the impact of the open banking framework on the activity of TradFis, showing the relation of the syndicated loan market to data-sharing policy. The novelty of the paper lies in an analysis of the syndicated loans market in relation to the introduction and adoption phases of the open banking framework. The syndicated loans market is a suitable empirical setting to study the overall effect of open banking frameworks in different European contexts and with different regulatory enforcement. Nevertheless, the intervention of the Payment Services Directive 2 (PSD2) is not limited to consumer payment data but also involves commercial business information, which is crucial in the syndicated loans market.

The paper uses a staggered difference-in-differences (DiD) approach to study the different phases of open banking development in the European Union (EU) that have introduced open banking frameworks in the member states. The first part of the analysis focuses on introducing the regulatory framework. It shows how payment service providers increasingly mitigate information asymmetry frictions in the credit application process, leading to lower loan interest rates without affecting the collateral after the policy intervention. At the same time, the second part of the main results on national-level adoption of the PSD2 shows that syndicated loan market characteristics and the fragmentation of EU regulation reduce the long-term effects of data-sharing policies. This mismatch in the effect of the PSD2 in the different phases of open banking development highlights the essential role of regulators in driving policy implementation. Furthermore, an alternative identification strategy based on European Banking Authority (EBA) data examines the direct development of APIs across the introduction and adoption phases of PSD2, studying the effect on banks that own third-party providers (TPPs). Additional, the study goes deeper in its analysis of different approaches to implementing open banking by looking at the case of the United Kingdom (UK) to investigate the effect of direct enforcement of data-sharing standards. Indeed, the UK has defined rules for its nine largest banks to enforce the open banking framework with a mandatory regulation standard for implementing technological infrastructure for data-sharing. This specific empirical setting confirms previous results that direct regulatory enforcement slows down the long-term effects of data-sharing policy. Last, following previous studies, to control for possible spillover effects in the syndicated loan market, the paper analyses the effect on shadow banks as financial intermediaries beyond the scope of the PSD2 (Buchak et al., 2018; Irani et al., 2021

The structure of the paper is as follows. Section 2 reviews the literature on hard and soft information in the context of open banking and syndicated loans. Section 3 on the institutional background explains the particularity of policy interventions in Europe. Section 4 provides hypothesis development as support for the empirical analysis. Section 5 describes the sample characteristics, the empirical strategy and the methodology. Section 6 provides the main findings, Section 7 that include robustness tests and Section 8 concludes with the policy implications of open banking frameworks.

2. Related literature

This paper contributes to the interplay among different related streams of literature that explore the role of regulation in driving the evolution of financial innovation, with the syndicated loan market being the setting of the analysis. First, the paper uses the literature on soft and hard information as a theoretical lens to analyse the impact of emerging technology on the lending activity of financial intermediaries (Liberti & Petersen, 2019).[2] How information asymmetry affects borrower and lender relationships has been extensively studied. Technology has been found to be the common factor mitigating friction in the lending process. Pagano and Jappelli (1993) discuss how information sharing increases lending volumes with information technology reducing adverse

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[2] Soft and hard information are defined as follows. (i) Soft information is communicated and transmitted by text (e.g. opinions, ideas, rumours, economic projections, statements of management future plans, and market commentaries). (ii) Hard information is recorded as numbers (e.g. financial statements, histories of payments that were made on time, stock returns and the quantity of output) (Liberti and Petersen, 2019).

selection and moral hazard. Improving the information technology structure generates spillover effects in the market, which raise competition and benefit customers (Hauswald & Marquez, 2003).

Different types of lending activities have been defined in terms of their information flows, showing how the ability of banks to acquire and monitor borrowed information is crucial to gain a competitive advantage in the market (Sharpe, 1990; Rajan, 1992; Boot & Thakor, 2000). Several studies have investigated the distinction between relationships and transactional lending, in the first case studying the role of uncodified soft information as the determinant of access to credit, and in the second how structured data as hard information can automate the lending activity. Indeed, small banks appear to have competitive advantages in lending based on soft information and financial constraints on small businesses (Berger, et al., 2005). Additionally, geographical proximity is one of the main channels driving capacity to reduce the opacity of private information. However, credit-scoring technology can only capture partial soft information (Agarwal & Hausewald, 2010). This competitive advantage of small institutions that leverage soft information by providing liquidity insurance in the market continues to be valid during periods of financial distress (Bolton et al., 2016; Berger et al., 2017).

The dichotomous duality between soft and hard information is changing with the recent development of emerging technology that leverages the mass of data generated in the last decade, leading to some financial intermediation theories needing to be re-written (Liberti & Petersen, 2019; Thakor, 2020; Boot et al., 2021). Switching to adopting and developing emerging technology that relies on hard information requires substantial investment. Indeed, it has been shown that banks have raised their spending on communication IT to respond to increased demand for small business credit to enhance their ability to transform soft information into hard information (He et al., 2022). This technological evolution has led to a stream of research exploring the connection between data flows and lending among traditional and fintech intermediaries. Puri et al. (2017) open the black box of banks' relationships with their customers and their links with payment systems, and reveal the mechanism behind using private data for credit assignment. Their results constitute evidence of banks needing historical data to screen borrowers, highlight how internal ratings can capture private information through payment information and reduce the default probability rates of given loans. On the fintech lending side, the role of private data in credit scoring technology has been considered, and it has been shown how digital footprints in e-commerce are reliable predictors of default rates, which can improve information on credit bureau scores (Berg et al., 2020). Consistent with this evidence is the effect of machine learning and big data on the use of credit scoring in the mortgage lending market provided by a fintech that can predict losses and defaults better than traditional models (Gambacorta et al., 2019; Fuster et al., 2019; Fuster et al., 2021). Emerging technology also raises attention to regulation arbitrage and issues that arise with the market entry of new non-regulated specialised business models, highlighting the role of regulation in taking care of these novel sources of risk that threaten financial stability. Buchak et al. (2018) investigate the growing phenomenon of shadow banking generated by controls by authorities of TradFis and how this may have encouraged the rise of alternative lending solutions that are less supervised. Di Maggio and Yao (2021) show that fintech lenders approve loans to borrowers with higher credit scores and lower debt-to-income ratios than traditional lenders. Fintech lenders also charge these more creditworthy borrowers lower interest rates. This evidence provide insights into the lending practices of fintech lenders and highlight the potential trade-offs between credit access and risk management in the fintech market.

Building on this literature on the nexus between payment data and lending, theoretical studies have started to investigate the open banking model, exploring the effect of data-sharing policy on the credit market, and highlighting the centrality of data as a reward for financial intermediation. Parlour et al. (2022) show the impact of open banking on innovation in payment processors and financial service providers and suggest that policy adoption has increased competition in the payment service market, leading to increased innovation and lower customer service costs. The mechanism behind data sharing affects competition in the credit market when borrowers own their financial data and share them with third-party lenders to access a broader range of novel credit options (He et al., 2023). Data sharing in open banking has become a crucial element stimulating the development of fintech firms and their entry in the market, showing that customer data access is one of the fundamental drivers of growth in financial innovation and inclusion (Babina et al., 2024). Once again, the initial empirical evidence of the impact of open banking originates from the fintech sector, and reveals that borrowers with a higher level of risk and lower credit scores willingly share their data. This leads to increased probability of loan approval and a reduction in interest rates (Nam, 2023). However, this type of regulatory framework should follow a country-specific approach in defining the policy objectives for fintech competition in relation to the current stage of development of the market and technological infrastructure.

This paper contributes to the literature with an empirical analysis of the introduction of open banking regulation in TradFis credit markets. On the one hand, the results show that access to credit has been improved thanks to the effect of competition created by data-driven policy interventions, and they highlight the role of regulators in supporting financial innovation and developing infrastructure enabling technology. On the other hand, the paper explores the complexity of the different phases in data-sharing policy interventions, and shows that the competition effect occurs when open banking frameworks are introduced at the European level and not implemented at the national level.

The context of the empirical analysis in this paper is the vast syndicated loans literature. Information asymmetry, market power and gaps in cross-country capital regulation are fundamental in the literature on pricing mechanisms in the syndicated loan market. Starting with the work of Dennis and Mullineaux (2000) on the relationship between loan characteristics and decisions to syndicate, it has been shown that loans with higher borrower credit risk and more complex loan structures are more likely to be syndicated. Indeed, Dennis and Mullineaux note that syndicated loans tend to have lower spreads than comparable bilateral loans due to the benefits of diversifying information on the lender. This effect on information asymmetry also arises in syndicated loan structures (Ivashina, 2009). It has been discovered that bank market power can facilitate access to credit by lower-performing firms (Delis et al., 2017). At the same time, gaps in cross-country capital regulation can influence syndicated loan pricing, which is more prevalent in countries with tighter capital regulation as lenders seek to diversify their portfolios and reduce risk (Gao and Jang, 2021). A recent study by Demiroglu et al. (2022) indicates that private information asymmetry can result in loan spreads being less responsive to changes in open market rates and observable firm credit risk characteristics. This is because lenders may seek compensation for the risk associated with not having complete information about the borrower's creditworthiness by adjusting loan spreads more rigidly. This paper also contributes to the syndicated loans literature by showing that data-sharing policy impacts the information structure of this market and mitigates borrower and lender frictions despite the particular characteristics of the market.

3. Institutional background

Regulators and supervisors encourage the adoption of open banking frameworks to create secure data-sharing infrastructure with application programming interface (API) technology to improve market competition and access to financial servers. This model has been designed and implemented with heterogeneous approaches and policies in different jurisdictions, showing that the journey to unlock the value of data in financial intermediation is only starting. The diverse levels of market maturity require different policy objectives in the regulatory frameworks. Developing countries implement open banking to give access to essential financial services such as bank accounts and digital payments to improve financial inclusion. In Europe, the same policies are introduced to reduce barriers to market entry for fintechs facilitating financial innovation. Behind this fundamental difference in policy objectives, open banking frameworks face common challenges and obstacles in developing them, showing that regulation is a crucial driver developing enabling technology infrastructure for data-sharing. It is possible to distinguish between two main approaches to open banking and financial innovation (BIS, 2019). The first involves market-driven innovation in jurisdictions that have decided not to adopt a rule-based approach and have not enforced explicit regulations on data sharing, leaving the market free to develop by itself. This is the case of the US, which has financial and innovation markets that are usually more prone to taking risks, leading to the definition of only principle-based guidelines and recommendations on data-sharing standards rather than an actual regulatory framework for open banking. The California Consumer Privacy Act (CCPA), which took effect on 1 January 2020, serves as a noteworthy policy example at the state level in the United States. It was enacted to empower consumers in their data ownership and the privacy of their personal information during a time marked by escalating data sharing. Unlike an open banking framework, the CCPA is more akin to the General Data Protection Regulation in its emphasis on safeguarding consumers' private information (Aridor et al., 2022; Doerr et al., 2023). The second approach is regulatory-driven innovation, which is based on prescriptive rules with different levels of enforcement of framework implementation. This is the case of Europe, where regulations have become essential tools enabling financial innovation, taking care of the emerging risk that comes from technology and stimulating growth in the market. Specifically, with the introduction of the PSD2 regulators focused their attention on two major policy objectives: to improve customer security in data portability and to increase competition in the market. The PSD2 introduces TPPs as regulated intermediaries accessing TradFis data, first to avoid screen-scraping practices, which are clearly defined in the data sharing process, and second to improve competition in the market by forcing TradFis to open data sources by implementing API technology.[3] Following the introduction of the PSD2, there are now more than 400 TPP authorities in Europe (EBA, 2023). This technical data-sharing protocol provides the infrastructure for interoperability between TradFis and new entrants such as fintechs (by both ‘building on’ it and ‘building with’ it), which enables them to put innovative financial services and products on the market. It allows fintechs to access large TradFis customer datasets, thus solving market scalability problems. At the same time, TradFis can take advantage of low-cost channels for marketing, and lower research and development costs by using fintech solutions to improve economies of scale and scope. This approach to innovating financial intermediation is aimed at developing and diffusing

[3] Screen scraping is the process of collecting display information from a ‘screen’ (typically a webpage) to use elsewhere or perform actions that the user would generally carry out. This was the technical solution to access payment information from consumer accounts before the introduction of the PSD2.

embedded finance. TradFis become not only platforms but also an ecosystem in which data sharing is the foundation for developing customer-centric solutions creating a win-win situation for TradFis and fintechs. However, adopting the PSD2 involved various challenges. On the one hand, a complete absence of reciprocity principles for nonfinancial institutions, such as BigTech, and remuneration incentives for TradFis to share their data with overblown costs for implementing API reduced the potential benefits of open banking. On the other hand, complexity of the European legislative process led to different national strategies to adopt the PSD2. The result was a slow transition to the industry adopting an open banking model. However, more recent policy developments encouraged a revision of the current directive into PSD3 to improve customer protection and API standardisation, a policy discussion on designing an open finance framework at the EU level and the Consumer Financial Protection Bureau in the US proposing an open banking rule.

The United Kingdom (UK) took a unique approach to implementing an open banking framework to unlock data-sharing and interoperability of data-driven innovation (Dinckol et al., 2023). It created an Open Banking Implementation Entity (OBIE), a dedicated institution established by the UK's Competition and Markets Authority (CMA) to develop open banking standards and promote competition and innovation in the financial services industry. The OBIE defined a regulation on the implementation of API technology and imposed direct enforcement on the nine largest banks in the UK (the CMA9).[4] This approach to open banking through the CMA9 is substantially different to that in other European jurisdictions, where harmonisation of technical API standards is delegated to market initiatives such as the Berlin Group.[5] The debate on the efficacy of the regulatory-driven approach is still open in jurisdictions like Europe, which is characterised by a higher level of regulatory and supervisory fragmentation requiring a holistic approach to developing a common market for financial innovation. Identifying the right balance between competition and market stability and integrity, however, is fundamental in the future design and revision of data policy interventions in the regulatory fragmentation of the European Union.

Overall, open banking is just a first experience in designing data-sharing policy in the financial intermediary market. Based on experiences of open banking regulations unlocking the value of

[4] The nine UK banks in the CMA9 are: AIB Group (UK) plc trading as First Trust Bank in Northern Ireland, Bank of Ireland (UK) plc, Barclays Bank plc, HSBC Group, Lloyds Banking Group plc, the Nationwide Building Society, Northern Bank Limited, trading as Danske Bank, The Royal Bank of Scotland Group plc and Santander UK plc (in Great Britain and Northern Ireland).

[5] https://www.berlin-group.org/psd2-access-to-bank-accounts

payment data, policymakers are already starting an extensive debate on creating open finance frameworks to extend the open data domain to all financial sectors.

4. Hypothesis development

This section combines academic theoretical and empirical literature with the institutional background related to the development of the open banking framework to formulate hypotheses on the impact on the lending markets which are tested empirically in the paper. The theoretical literature analyses the main policy objectives of open banking frameworks and studies the repercussions of data-sharing competition in payment services and its broader effects on the financial intermediaries and lending market. It highlights how competition disrupts the information advantage held by a monopolistic bank, leading to adjustments in pricing for payment services and ambiguous effects on consumer welfare in the loan market (Parlour et al., 2022; DeFusco et al., 2022). Open banking enhances information efficiency in borrower selection and strengthens the screening capabilities of fintech players. Nevertheless, it also introduces a strategic dimension to market competition. If open banking intensifies competition it tends to favour borrowers with high credit quality. Conversely, if it excessively empowers fintech firms it can curtail competition, adversely affecting all borrowers (He et al., 2023). However, given that open banking is a two-sided market in which regulation intervention has played a crucial role in deterring the impact of policy interventions by defining clear rules for regulatory frameworks, the information efficiency effect should also impact TradFis and the effect should not be limited to the fintech side (Boot and Thakor, 2000). Indeed, TradFis under open banking regulation are affected by increased data availability in their pricing process, in which hard information becomes predominant (Liberti & Petersen, 2019; Boot et al., 2021). This theoretical foundation and policy reflation drives the formulation of the first hypothesis.

H1. Open banking regulation improves data sharing and portability, reducing information asymmetries in the loan market.

The second hypothesis considers the specific syndicated loan market in the dynamics of the competition effects created by the open banking regulation on data availability. In the syndicated loan market the effect of competition on the information efficiency created by the regulatory adoption of an open banking framework can be limited to the short term or be less effective in the long term. Indeed, the economic impact on loan spreads is significant due to the information asymmetry problem in a syndicate (Ivashina, 2009). On the one hand, the stickiness of the syndicated loan market in adjusting to private information can reduce the effectiveness of data-sharing policy, continuing to reflect mispricing of the loan interest rate (Demiroglu et al., 2022). On the other hand, soft information continues to play an important role in the negotiation phase of the syndicated loan even when information efficiency relative to sharing hard information has been established (Berger et al., 1992; Dougal et al., 2015). Indeed, intermediaries under an open banking framework have the possibility to access the same hard information to observe the credit quality of borrowers through the data-sharing competition mechanism. This underlines the fact that the efficiency effect on information asymmetry related to hard information that can be observed in the short term might in the long term be overcome by the crucial role of soft information in the pricing mechanism of the syndicated loan. This leads to the second hypothesis on the efficiency of regulatory support in creating the long-term effects of data-sharing policies.

H2. Partial adjustment of the syndicated loan price to private information sharing reduces the long-term effect of implementing open banking.

From the policy perspective, the active role of regulators in implementing open banking frameworks is essential to establish a regulatory-driven innovation approach. Regulators should proceed with simple regulatory interventions and design a dedicated strategy to reduce technical and market barriers against the development of technological architecture. Indeed, the theoretical economic benefits described in the literature need to take into account the cost of implementing technology and the regulatory complexity behind open banking frameworks in a context such as Europe. In the case of the PSD2, enforcement of regulatory frameworks followed country-specific characteristics without a common European framework for implementing harmonised API infrastructure and limiting cross-border interoperability (Babina et al., 2024). This fragmentation raised regulatory uncertainty about the specific enforcement and development of open banking frameworks. At the same time, the PSD2 only imposes the cost of investing in technological infrastructure on TradFis without there being a remuneration mechanism for data-sharing (He et al., 2022). This paper delves into the dynamics of the syndicated loan market and explores the interplay between information efficiency and data-sharing policies. It takes a deeper dive by investigating the influence of regulatory-driven innovation approaches on TradFis. In the end, understanding the effects of different approaches to regulatory enforcement is essential in order to understand the role of policymakers in supporting financial innovation.

5. Data and empirical strategy

In this section the data collection process for the sample and how it is structured are first described. Next, the identification strategy to support policy exercises and the empirical challenges in evaluating the impact of PSD2 are explained. Finally, a staggered DiD model to test the previously developed hypotheses on the effect of data-sharing frameworks in the syndicated loan market is presented.

5.1. Data description

To study the effect of the introduction and development of open banking this paper uses the syndicated loan market in Europe as the analytical setting. This allows testing of the hypotheses using loan-level data from credit institutions in different member states to study the heterogenous effects of PSD2 in the different stages of introducing the open banking framework. The sample includes observations in both Europe and the UK to reflect the dynamics of European legislation, which the UK was involved in before Brexit. Indeed, the European Union's (EU) legislative process is characterised by two major steps which lead to the adoption of a directive at the national level. The first step is approval of a European directive by the European Parliament and Council. This step is typically followed by a time frame for member states to adopt the directive as national law by means of their legislative processes. To cover this administrative time the sample goes from 2014 to 2020 to capture the effect of the introduction of the PSD2. The directive was approved at the EU level on 12 January 2016 and it was mandatory for the member states to adopt it by 13 January 2018. The sample is restricted to 2020 to leave out the period of the pandemic shock, which could affect the results. The loan-level data are collected from Thomson Reuters's Dealscan database, which contains information on the syndicated loan market. The sample contains loans issued to firms in the same country as the lending institutions. This identification process excludes cross-border lending activities, which are affected by nationally heterogeneous policy interventions. The data are matched with borrower and lender control variables, which are respectively collected from Orbis and BankFocus using linking panels constructed for the EU area following the approach of Chava and Roberts (2008) and Schwert (2018). The sample also includes the Standard Industrial Classification (SIC) codes to identify depository institutions as central reserve depository institutions, commercial banks, savings institutions, credit unions, branches and agencies of foreign banks and functions related to depository banking (Lim et al., 2014).[6] This identification strategy supports the empirical analysis by distinguishing between depository institutions like banks and non-depository institutions like shadow banks, hedge funds, private equity funds, mutual funds and pension funds (Buchak et al., 2018; Irani et al., 2021). The TTP data is collected from the EBA registers of authorized entities and manually merged with the information hand-collected from the Open Banking Tracker database, which includes details on API implementation by banks.[7]

Table 1 shows the distribution of the loan markets by country and includes the date of adoption of the PSD2 in each member state. The information was manually collected from national state law records. It is evident that each state decided to adopt the PSD2 at different times before or after the deadline of 13 January 2018. Indeed, the implementation periods distinguish between early treatment before the deadline for the adoption of the PSD2, treatment at the time of the deadline and late treatment after adopting the open banking policy. This is essential for an empirical design based on recent advances in the difference-in-differences literature to analyse the heterogeneous treatment effects on the different cohorts according to the variation over time of the adoption of the PSD2 by each member state, as is reported in the last column of Table 1 (Roth et al., 2023). Ultimately, this empirical setting aims to disentangle the heterogeneity effect of the policy adoption in the regulatory intervention, which is essential to understand the market dynamics over time.

[INSERT TABLE 1 ABOUT HERE]

5.2. Descriptive statistics

This section presents descriptive statistics of the overall sample, including the characteristics of the loans, lenders and borrowers in the different phases of adoption of the PSD2 and in the subsample. Table 2 shows the 4877 observations in the sample with the division into sub-samples and the differences in the means of the characteristics of the two specifications. First, in the sub-samples financial intermediaries covered by the PSD2 such as banks and institutions outside the regulatory framework such as shadow banks are distinguished. Furthermore, column (3) shows that on average shadow banks have larger loan spreads associated with higher collateral and covenants, which highlights the fact that lending is riskier for non-deposit institutions. This result aligns with

[6] The SIC codes of the institutions in the sample are 6011, 6019, 6021, 6022, 6029, 6035, 6036, 6061, 6062, 6081, 6082, 6091 and 6092.
[7] https://www.eba.europa.eu/risk-and-data-analysis/data/registers/payment-institutions-register; https://www.openbankingtracker.com/

the literature on the rise of shadow banks in the syndicated loan market as non-regulated credit institutions that leverage capital requirements underlying possible regulatory arbitrage threats (Irani et al., 2021; Buchak et al., 2018). Second, differences between UK bank loan issuers in the CMA9 and other banks in the sample are examined. The rationality behind this is that it is essential for the empirical analysis to identify the effect of prescriptive enforcement of the open banking framework. Indeed, after introducing the PSD2 the UK was the only country that adopted a mandatory open banking framework for the development of API among TradFis, with the creation of the OBIE and the definition of the CMA9. Columns (4) to (6) report repayments by the sample to CMA9 banks enforced by the OBIE and the other banks exposed to the PSD2. There are non-significant differences in the loan spread among them. However, the CMA9 banks have significantly bigger loan sizes, leverage, fixed assets and net income than the EU ones, underlining the fact that UK open banking enforcement is for big financial intermediaries.

Table 3 shows differences in the mean for each step in the PSD2 legislative process, starting with the introduction phase in columns (1) to (3), moving to the adoption phase before the deadline for member states to introduce the directive in their regulatory framework in columns (4) to (6) and ending with the actual date of adoption of the PSD2 by each member state indicated in Table 1 in columns (7) to (9). In the sample specification used to support the development of the empirical strategy, introducing and adopting the PSD2 have average significant effects on the loan spread between 1.42% ($p < 0.01$) and 0.97% ($p < 0.01$). Furthermore, looking at the other loan characteristics, collateral and covenants are significant in the PSD2 implementation phase, which is consistent with evidence in the literature that loans become less collateralised when more borrower data are available (Gambacorta et al., 2023). Finally, the overall dynamics of the lender characteristics exhibit a significant reduction in leverage and an increase in net income. At the same time, borrower characteristics significantly differ in leverage and fixed assets. The heterogeneity of the loan, borrower and lender characteristics is crucial to determine a robust estimation in the staggered DiD analysis.

[INSERT TABLE 2 ABOUT HERE]

[INSERT TABLE 3 ABOUT HERE]

5.3. Empirical design

The empirical design of this study mirrors the introduction and adoption of the PSD2 directive in the EU. The methodology encompasses several steps, beginning with an analysis of the overall effectiveness of the policy intervention, followed by a study of country-specific variations in PSD2 enforcement during the adoption phase and culminating in robustness tests employing alternative identification strategies.

The paper uses staggered DiD methodology with several different empirical settings following the most recent advances in the econometrics literature on studying multiple treatments with different treatment times (Roth et al., 2023). As was previously mentioned, the PSD2 entered into force following a complex legislative process. From an econometric perspective, identifying the effects of the PSD2 is an empirical challenge. The first part of the analysis is a standard event study exploring the single effects of the introduction and adoption of the PSD2 to understand the effectiveness of the policy intervention in the different phases of the EU legislative process. Two-way fixed effects (TWFE) regressions are performed on the empirical models to estimate the treatment effect after introducing and adopting the PSD2. The model estimated in the first part of the analysis is equation 1.

$$Y_{b,f,t} = \beta_1 PSD2 + \beta_i L_t + \beta_i B_{b,t-1} + \beta_i F_{f,t-1} + \varphi_{f,b} + \rho_{b,t} + \gamma_{f,t} + \epsilon_{b,f,t} \quad (1)$$

In equation 1 $Y_{b,f,t}$ is the logarithmic transformation of the spread of a loan facility to firm *f* by bank *b* at time *t* over the LIBOR or dichotomous variable, which takes value one if the loan is collateralised and zero otherwise. The dummy variable $PSD2$ has different specifications for each of the three phases in the legislative process. In the introduction period its value is zero until 12 January 2016 and one afterwards. In the adoption period it is zero until 13 January 2018 and one afterwards. L, B and F are vectors of loan, bank and firm characteristics that can affect the dependent variable. The regression model is saturated by adding different combinations of fixed effects to control for possible sources of endogeneity that can affect the results. $\varphi_{f,b}$ is a firm∗bank fixed effect to roll out pre-existing long-term lending relationships that might affect the information asymmetry with the firms and relationships and additional bank characteristics, $\rho_{b,t}$ is a bank*quarter fixed effect and $\gamma_{f,t}$ is a firm*quarter fixed effect to capture possible changes in the supply of credit and demand determined by macro factors or other sources of endogeny. The model includes clustered standard errors at the bank level to account for serial correlation in the same bank and at the same time related to the level of the policy intervention shock. Lag controls and fixed effects are included in the model following different specifications to avoid multi-collinearity problems.

The staggered approach is implemented following the setting of equation 1 with dummies introduced as the interaction variable for each member state, and the time of adoption of the PSD2 is constructed using the data in Table 1 to define the average treatment effect in the countries. The variable is zero until the date of adoption of the PSD2 and one afterwards. However, the TWFE staggered DiD regression estimations can be biased by treatment effect heterogeneity (Baker et al., 2022). First, the staggered treatment is decomposed for the different cohorts in Table 1 to reduce this possible estimation bias. Furthermore, the average treatment effect for all the cohorts is estimated following the methodology in Callaway and Sant'Anna (2021).

Second, the analysis continues with a quasi-natural experiment with a 2x2 DiD approach to find the heterogeneous effect of introducing the PSD2 at the national level by looking at the subsample of the early treatment cohort that includes UK CMA9 rules as the enforcing mechanism to adopt open banking frameworks. The rationale behind this is to compare the UK as the unique case of application of restrictive prescriptive rules with adoption of the PSD2 in the EU. Equation 2 is the second main model in the empirical strategy to inquire into the effect of the UK approach to implementing an open banking framework. The DiD regression model is:

$$Y_{b,f,t} = \beta_1 PSD2 + \beta_2 Treatment + \beta_3 PSD2 * Treatment + \beta_i L_t + \beta_i B_{b,t-1} + \\ + \beta_i F_{f,t-1} + \varphi_{f,b} + \rho_{b,t} + \gamma_{f,t} + \epsilon_{b,f,t.} \qquad (2)$$

This is equation 1 with interaction terms introduced. In the staggered decomposition analysis $PSD2 * Treatment$ is the product of the post-treatment period and the group dummy, $PSD2$, which for the introduction period is zero until 12 January 2016 and one afterwards, and following 19 September 2017, the implementation date of the OBIE standards, is one for the treatment group if the loan is made by one of the UK CMA9 banks and zero otherwise. If the loan is made by an EU member state *PSD2* is the relative dummy Furthermore, the same analysis framework as described in Equation 2 will be applied to examine banks' direct adoption of API technology, aiming to better identify the effects of PSD2 on the syndicated loans market.

The other specifications are the same as for equation 1. As an additional robustness test this model is also used as a particular specification in which shadow banks are the control group for the DiD analysis since they are not regulated under the PSD2.

6. Results

This section presents the results of the previously described empirical analysis following the methodological steps to identify the impact of open banking frameworks on TradFis lending. Before presenting the main empirical results, it first focuses on a graphic analysis related to the parallel trends assumption to support the TWFE staggered DiD regressions approach.

Figure 1 displays the coefficient plot for equation 1 of the fixed effects with time frames for the different cohorts, which allows us to examine the heterogeneity effect of open banking frameworks across the EU. Zero represents the introduction of the PSD2. Panel A shows the dynamics of the year fixed effects for equation 1. A fully saturated model is employed that includes loan, bank and borrower controls, providing initial support for the parallel trends assumption for the different cohorts. Panels B and C respectively show the half-year and quarterly fixed effects. It is evident that the variation in the time variables is critical to identify the effect of the policy intervention. On the one hand, the decomposition of the staggered effect over the different cohorts reveals that late adopters tended to be more rigid compared to the rest of the sample, suggesting that the effects may be driven by countries that introduced the PSD2 with more stringent implementation before or on the deadline for the adoption of the EU directive. On the other hand, the information asymmetry effect of open banking becomes apparent after the first half-year after the introduction of the PSD2. This may be driven by the costs associated with TradFis implementing API technology (Agarwal & Hausewald, 2010; He et al., 2022). Overall, this initial part of the graphical analysis shows the dynamics of the fixed effects over the heterogeneous effects of the different cohorts over time in introducing the PSD2 at the EU level, highlighting the complexity and fragmentation involved in creating new regulatory frameworks.

[INSERT FIGURE 1 ABOUT HERE]

6.1. Main results

The empirical model results for equation 1 are reported in Table 4, which shows the different stages of introducing and adopting the PSD2 estimated using the sample TWFE event study model. Columns (1) to (6) show the PSD2 introduction phase, with the dummy variable in the DiD considering 12 January 2016 as the policy event for the two variables of interest, the logarithmic transformation of the spread and the collateral. Column (1) shows the result for the simple regression model with all the fixed effects to absorb the missing firm and bank control variables. This is the first evidence supporting the hypothesis that the overall effects of the PSD2 indicate a reduction in loan interest rates. Specifically, the interest coefficient indicates a high statistically significant reduction of -5.28% ($p < 0.01$). Columns (2) and (3) show the effects of additional controls for supply and demand driving this preliminary result. Column (2) shows the estimation with borrower controls and the same structure of fixed effects for possible demand shocks over time. This result is consistent with the first evidence and it indicates a statistically significant reduction of -7.67% ($p < 0.01$). Column (3) shows the result for the fully saturated model with bank controls and bank and fixed effects to check for additional exogenous variation over time. The result is coherent with the first estimation, a significant negative reduction of -3.62% ($p < 0.05$) of the interest loan rate. Furthermore, columns (3) to (6) show the effect of PSD2 in the introduction phase, showing how it is limited to the loan spread without a significant impact on the collateral structure. This initial part of the analysis confirms the first hypothesis that the open banking framework improves access to the credit market by reducing the loan interest rate. These findings are coherent with findings in the theoretical literature that payment provider competition is a mechanism with which the credit market reduces information asymmetry through data availability and portability (Parlour et al., 2022; He et al., 2023).

Next, columns (7) to (12) show models with the same specification of control variables and fixed effects as the previous estimations that look at the adoption of the PSD2 using 13 January 2018 as the deadline for all the countries in the EU to implement the directive. Column (7) shows a highly significant positive coefficient for the simple regression model without bank and firm control variables, an increase of 4.53% ($p < 0.01$). Furthermore, estimations of the fully saturated models with borrower and bank control variables in columns (7) and (9) align with the result for the first model. They show significant positive coefficients that confirm an increase in loan interest after adoption of the PSD2 of 5.55% ($p < 0.01$) and 4.38% ($p < 0.05$). Regarding the collateral side, columns (10) and (12) show positive high coefficients of 0.0177 ($p < 0.05$) for the sample model with the complete set of fixed effects and 0.0194 ($p < 0.05$) for the one with additional bank controls. These are coherent with the result for the spread. The non-significant effect of the model reported in column (11) suggests that the effect on collateral might be absorbed by the firm characteristics and reduced information asymmetries, showing that data can reduce the use of collateral in the loan market (Ioannidou et al., 2022; Gambacorta et al., 2023).

The results of the second part of the analysis that focuses on the adoption phase of open banking frameworks suggest an adjustment in the syndicated loan market. The information efficiency resulting from the competition effect of the PSD2 is reflected in the syndicated loan market with an opposite effect in the long term. This result underlines the mechanisms behind the second hypothesis that TradFis continue to rely on private and soft information and partially adjust to borrower characteristics (Demiroglu et al., 2022). However, from a policy perspective, the long-term effect of adopting open banking shows that European fragmentation could create a mismatch between the introduction of the European directive and policy implementation that limits the benefit from developing data-sharing frameworks. On the one hand, to unlock the full potential of open banking a structured approach is needed to implement the policy in the medium and long term beyond simple enforcement of the regulation at the national level. On the other hand, regulatory uncertainties that characterised the adoption of the PSD2 in Europe increased the infrastructure and compliance costs of TradFis, leading to a slow effect on the interest rate dynamics in the credit market. This policy consideration can better explain the limited effect of the data-sharing policy on the syndicated loan market.

[INSERT TABLE 4 ABOUT HERE]

6.2. Staggered analysis

The analysis proceeds by looking at the implementation phase of open banking frameworks, which had heterogenous effects across the EU. Indeed, as was mentioned before, adoption of the PSD2 occurred at different times. This is reflected in the empirical challenges discussed in the previous methodology part. Table 1 shows the details for each member state to control for the possible anticipation or delay in the effects of the policy intervention and to distinguish treatment countries that adopted the PSD2 before and after the deadline. The decomposition of the overall effect of the different cohorts over time is implemented following Wooldridge (2021) to look at the dynamics of different treatments. Starting with the setting of equation 1, the comprehensive effect of the staggered treatment determined by the interaction terms to identify the overall sub-sample of loans exposed to PSD2 adoption is decomposed into the effects with interaction terms for early adoption, on-time adoption and post-treatment, together with the time to treatment and the full sub-samples treated to decompose the average effect of the staggered interaction terms. This approach aims to reduce a possible estimation bias in the staggered DiD setting resulting from variation in treatment timing (Goodman-Bacon, 2021; Baker et al., 2022; Roth et al., 2023).

Before presenting the decomposition of the results, Figure 2 illustrates the dynamics of various cohorts over the course of implementing the PSD2 following the specifications of the comprehensive models incorporating loan, bank and borrower controls as in Figure 1. This preliminary evidence shows the variability across the sub-sample for different treatment times – Q3-2017, Q1-2018 and Q4-2018 – which could potentially impact the estimation of the average treatment effect. Panels A to C display the coefficients of the quarterly fixed effects alongside the corresponding PSD2 implementation times, showing the different times of adoption of the PSD2 that could create an anticipation effect in the average treatment effects. The early treatment period depicted in Panel A exhibits significantly higher time variability than treatment at the deadline and afterwards, as illustrated in Panels B and C respectively. This illustration highlights how the main effects are related to the introduction phase of PSD2 and not the adoption phase. However, countries that enforced the open banking framework at the natural deadline of the directive and slightly thereafter do not exhibit significant variations in interest rate dynamics. This graphical representation supports formulation of a second hypothesis that the syndicated loan market is inflexible in its adjustment to data-sharing policies in the long term. Nevertheless, the following estimation methodology aims to reduce the possible effects of the treatment time heterogeneity on the outcome variables.

[INSERT FIGURE 2 ABOUT HERE]

Moving to the empirical analysis, Table 5 reports the results for different settings of the staggered analysis. Columns (1) to (6) show the comprehensive effects of adopting the PSD2, including early treatment based on the specification of the equation 2 regression model. Consistent with the first analysis, in column (1) the sample regression model without control variables shows a significant positive increase in the loan interest rate of 5.13% (p <0.01). Following the structure of the second part of the previous analysis, in columns (2) and (3) saturated models with control variables show significant positive increases in the loan interest rate of 4.85% (p <0.01) and 4.71% (p <0.05). Furthermore, the results for collateral in columns (4) to (6) are consistent with the previous initial analysis shown in Table 4.

Moreover, the decomposition of the dynamic effect of the staggered DiD analysis in column (7) shows significant positive coefficients for cohorts that adopted the PSD2 on the exact deadline and for countries that implemented the directive late. In the first case, the increase in the loan interest rate is estimated at 13.52% (p <0.01) and in the second one 3.79% (p <0.01). These results are consistent with the model in column (8) with borrower controls that shows increases of 13.54% (p <0.01) and 3.35% (p <0.1). The results for the saturated model in column (6) indicate that the main effect comes from cohorts that implemented the policy on the deadline, indicating an increase consistent with the previous estimation of 14.93% (p <0.01). Column (10) indicates positive highly significant coefficients for the deadline and late treatment of 0.0168 (p <0.1) and 0.0112 (p <0.1) respectively. This second part of the analysis of the enforcement of the PSD2 shows how open banking frameworks are fragmented at the EU level. This regulatory fragmentation plays a substantial role in the long-term outcomes of unlocking the value of data in creating a more digital and efficient financial system.

[INSERT TABLE 5 ABOUT HERE]

Furthermore, to address potential estimation biases arising from differences in observed characteristics that could lead to non-parallel outcomes among treated cohorts, this section employs inverse probability weighting (IPW) and doubly robust estimations (Callaway and Sant'Anna, 2021). Following the methodology proposed by Sant'Anna and Zhao (2020) for doubly robust estimators in DiD research designs, Table 6 presents the decomposition of staggered effects across the different cohorts using all the estimation methods. In specific detail, Table 6 displays results for doubly robust DiD with wild-bootstrap clustered standard errors at the bank level. The underlying estimations of the IPW DiD model in Abadie (2005) and regression-based DiD are also presented. Columns (1) to (3) focus on the first variable of interest, the logarithmic transformation of the loan interest spread. The subsequent columns from (4) to (6) examine the results pertaining to the presence of collateral. All the estimation models incorporate distinct control specifications for loan, bank and borrower characteristics, aiming to account for covariate structures that can influence DiD estimation outcomes. Examining the fully saturated models in columns 3 and 6 reveals that doubly robust DiD estimations generally exhibit a lower variance structure compared to regression-based DiD, showing that the estimation model considers treatment effect heterogeneity concerning continuous covariates of the controls. Regarding the magnitude of the effects, the results are aligned with the earlier discussion related to the second hypothesis, the notion that the open banking framework has limited effects in the long term due to the nature of syndicated deals and the role of private and soft information (Demiroglu et al., 2022; Berger et al., 1992; Dougal et al., 2015).

[INSERT TABLE 6 ABOUT HERE]

7. Robustness tests

The following paragraphs will present several robustness tests aimed at corroborating the preliminary evidence outlined in the main results. Specifically, the first set of alternative estimations examines the direct development of APIs across the introduction and adoption phases of PSD2. The second set delves into the direct enforcement of Open Banking frameworks, focusing on the UK case and its association with the CMA9 rules. Finally, the last set explores potential spillover effects of shadow banking on the syndicated loans market.

7.1. Alternative identification strategy

In this section, an alternative identification strategy is proposed to support the main results presented earlier in the PSD2 introduction. Based on EBA data, payment institutions have identified which banks utilize TTP as a proxy for the implementation of APIs. Furthermore, the EBA data is cross-checked with hand-collected data from the Open Banking Tracker database to verify which banks have actually developed an API. Indeed, this fundamentally tests the direct effect of open banking enforcement on the loan market for banks that have actually developed APIs for data sharing. The analysis in Table 7 is based on the first specification of the DiD empirical model represented in Equation 2, where the treatment group is constructed using the API dummy variable, which represents banks that have implemented an API. The remaining banks in the sample constitute the control group. The results of this additional estimation, presented from columns (1) to (6) in the introduction phase of the PSD2, are consistent with the previous evidence. Indeed, the results for the interaction terms of DiD, considered as variables of interest in columns (1) and (2), are negative and highly significant, indicating a reduction in the loan interest rate, approximately -3.01% ($p < 0.05$) and -4.17% ($p < 0.01$), respectively. Similarly, the non-significant collateral results align with the previous estimations. Moving forward to the analysis of the adoption phase of the open banking policy, the results from columns (6) to (9) are consistent, with the initial estimations showing a statistically significant increase in the interest rate ranging between 2.44% ($p < 0.05$) and 3.78% ($p < 0.1$) across the models. Furthermore, the estimations presented from columns (9) to (12) for collateral are consistent with the main results, highlighting a coherent increase in collateral in line with the rise in loan spread. This alternative estimation method, aimed at more accurately identifying API implementation by banks, substantiates the initial findings and elucidates the divergent effects observed between the phases of PSD2 introduction and adoption. This empirical evidence initially reinforces the hypothesized impacts of information asymmetry and the temporal dissonance between short- and long-term consequences, stemming from the inherent characteristics of the syndicated loan market and the regulatory fragmentation prevalent across various jurisdictions. Indeed, the absence of harmonized and consistent enforcement of open banking frameworks has significantly curtailed the efficacy of PSD2. The mechanism of market competition underpinning open banking adoption was notably hindered by the necessity for greater standardization in API development and incentives for TradFis to share their data.

[INSERT TABLE 7 ABOUT HERE]

7.2. The Competition and Markets Authority 9 rule

This section looks at the implementation of the OBIE open banking framework in the UK compared to the adoption phase of the PSD2 in the EU to analyse the implication of direct regulatory enforcement. Indeed, unlike the European countries, which left directionality to the market in the development of API technology, the UK with the CMA9 standards had stricter mandatory enforcement to implement regulatory frameworks to unlock data availability from the nine largest banks in the market. This was reflected in the UK context in stronger regulatory intervention requiring a higher initial outlay to set up open banking API infrastructure for TradFis. The 2x2 DiD empirical model represented in equation 2 aims to identify the differences from the most stringent rule of thumb for enforcing the implementation of the CMA9 standards for the banks in the open banking framework in the UK compared with the EU member states. Table 8 reports the results for the two variables of interest used in the previous analysis over the different steps in the regulatory implementation in the UK. First, columns (1) to (6) consider the deadline for compliance with the OBIE requirement for open banking technological infrastructure, taking the CMA9 banks as the treatment group and the rest of the sample as the control group. Second, concluding the overall picture of the implementation of PSD2 open banking frameworks, columns (7) to (12) show estimations of the difference in adopting the PSD2 in Europe. The results for the OBIE show significant coefficients only for the fully saturated models with bank controls and time, bank and firm fixed effects which are consistent with the previous findings. In more detail, the models in columns (3) and (6) show consistent increases in the loan interest rate of 13.38% ($p < 0.05$) and for collateral a value of 0.0750 ($p < 0.1$). This evidence related to the policy intervention in the UK shows that open banking is a supply-driven policy and underlines that the enforcement of regulatory frameworks could create a mismatch effect with an additional structural cost of full implementation of the API technology in the short term and benefits in the long term of the adoption of the technology (Hauswald and Marquez, 2003; He et al., 2022). Furthermore, the results of the models for the adoption of the PSD2 in columns (7) to (12) are consistent with the first part of the analysis, indicating the same positive significant coefficients for loan interest rate models in columns (8) and (9) of 5.20% ($p < 0.1$) and 12.14% ($p < 0.05$) respectively. However, the results in columns (10) to (12) of estimations of the collateral models do not show a significant impact after the adoption of the PSD2.

This evidence aligns with the initial phase of the analysis, reaffirming that the effects of the regulatory framework persistently diminish over time. Indeed, the case of the UK is coherent with literature that finds that different economic contexts should follow specific approaches in defined regulatory frameworks to achieve different policy objectives (Babina et al., 2024). The UK strategy is a long-horizon policy that started by imposing significant investments on TradFis to develop the open banking model by implementing API infrastructure. The prescriptive nature of the CMA9 rule created substantial cost and technical barriers that slowed its technological adoption. Nevertheless, the implementation of the OBIE policy strategy has been acknowledged as a successful endeavour gradually benefiting the market, yet it still has untapped potential. However, this could have created a difference compared to other types of loans, such as retail ones (Parlour et al., 2022; DeFusco et al., 2022).

[INSERT TABLE 8 ABOUT HERE]

7.3. Shadow Banks

This last part of this paper investigates the effect of introducing open banking frameworks on shadow banks. After the 2007-09 crisis, shadow banks started to play a significant role in the credit reallocation of the syndicated loan market (Irani et al., 2021). This phenomenon is primarily attributable to advances in technology, liquidity transformations and possession of superior knowledge. The impetus for nonbank entities to enter this market stems from these transformative factors (Buchak et al., 2018; Ordoñez, 2018; Moreira and Savov, 2017). The entry of nonbank players in the syndicated loan market holds the potential for more proactive risk allocation, heightened cost efficiency and reduced borrowing expenses for households (Fuster et al., 2019). The enforcement of the open banking frameworks could lead to an additional regulatory arbitrage shift (Buchak et al., 2018). However, at the same time, following the development of the hypothesis on information asymmetry, the introduction of the PSD2 could result in a spillover effect on the syndicated deal information structure.

The analysis follows the baseline regression model in equation 1 for non-deposit entities identified as shadow banks in the methodology section, the same time event structure as the first analysis for the introduction and adoption of the PSD2 and includes specific loan, borrower and lender controls plus fixed effects. Table 9 reports the results in columns (1) to (12) for the different phases of the open banking legislative process, replicating the first part of the analysis. The coefficients in columns (1) to (6) which consider the introduction phase of the PSD2 are not statistically significant, showing that only the adoption phase of the directive is relevant for shadow banking. Moving forward, columns (7) to (12) show highly significant and positive coefficients for all the saturated models that consider as the variable of interest the logarithmic transformation of the loan interest rate. This ranges from 5.66% ($p < 0.05$) to 10.47% ($p < 0.1$). This finding indicates that shadow banks react the same way as the market to the policy intervention, showing that the adjustment pricing mechanisms of syndicated loans in the second hypothesis affect the overall market. This effect can be transmitted to the deal structure of syndicated loans. However, borrower and lender information friction is still present in the arrangement mechanism, partly reflecting the adjustment to information sharing and underlining the important role of private information (Ivashina, 2009; Demiroglu et al., 2022).

These results are coherent with the previous part of the analysis, showing that data availability and portability are crucial components for financial intermediaries that also affect entities outside the regulatory perimeter of the data-sharing policy intervention. This is evidence of the fundamental role of regulation in designing policy interventions to enable financial innovation.

[INSERT TABLE 9 ABOUT HERE]

8. Conclusion and policy implications

This paper has discussed the role of regulation in facilitating financial innovation, looking at the effect of data-sharing policy on the credit market. Open banking frameworks exemplify how regulatory-driven innovation policy can be a fundamental driver fostering financial innovation, balancing market competition and ensuring financial stability in the data economy. The results of the analysis of the impact of the PSD2 on TraFiIs are coherent with the theoretical literature on open banking that shows that the mechanism behind the reduction of information asymmetry friction in the credit market by increasing competition among payment providers improves data portability and availability. On the one hand, the introduction of the PSD2 produces a reduction in the loan interest rate that suggests a potential effect of open banking on financial inclusion. On the other hand, the decomposition of the effect in the different phases of adopting the PSD2 shows that countries' specific approaches matter in establishing the long-term effect of data-sharing policies.

Furthermore, this paper has discussed how the syndicated loan market partially adjusts to information sharing, showing that specific deal characteristics and private information continue to play essential roles in the pricing mechanism. The ambiguous welfare effect of open banking on different types of loans should continue to be studied in future work, specifically large consumer credit loans by TraFiIs (Parlour et al., 2022; DeFusco et al., 2022).

From a policy perspective, a regulatory-driven innovation approach to open banking shows that technology neutrality is essential in the development of regulation on financial innovation that considers data privacy and consumer protection. However, this paper has shown that national fragmentation in a context such as the EU can slow down the effectiveness of policy interventions. This is one of the main regulatory challenges in harmonised frameworks for standardisation of API to improve cross-country and sector interoperability. Much work must still be done on this evolutionary path of financial innovation that puts data at its centre. Understanding the current state of the art of open banking frameworks is essential for the future development of open finance policy to unlock the actual value of data. A horizontal extension of data-sharing policy across all financial intermediation sectors outside banking increases the expositional complexity in the design of future frameworks. At the same time, enforcing these frameworks should follow a modular approach that respects vertical sector particularities in which collaboration between regulators becomes crucial to realise a common data-sharing policy for the financial sector.

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Table 1. The overall distribution of the sample by country including banks and shadow banks, specifying the date of adoption of the PSD2. The early, deadline and late treatment groups are shown, indicating the corresponding stage of PSD2 adoption.

Country	Observations	Date of PSD2 Adoption	Treatment groups
Denmark	27	08/06/2017	Treated Early
United Kingdom	652	19/09/2017	Treated Early
Finland	18	13/01/2018	Deadline Treated
Germany	534	13/01/2018	Deadline Treated
Ireland	129	13/01/2018	Deadline Treated
Italy	338	13/01/2018	Deadline Treated
Cyprus	33	18/04/2018	Treated Late
Austria	50	01/06/2018	Treated Late
Luxembourg	56	29/07/2018	Treated Late
France	1247	05/10/2018	Treated Late
Belgium	99	09/10/2018	Treated Late
Spain	1474	19/11/2018	Treated Late
Netherlands	220	05/12/2018	Treated Late
Total	4877		

Table 2. Summary sample statistics focusing on the difference in the means of the subsamples used in the analysis. The sample includes the following specifications: banks as deposit institutions; shadow banks as non-deposit institutions; EU banks operating in the European market; CMA9 – the nine largest UK banks adopting OBIE standards. The variables are defined as follows: Loan characteristics – Log(spread) is the natural logarithm of all-in-drawn spread over LIBOR plus the facility fee; Log(size) is the natural logarithm of the loan facilitated; Log(maturity); Collateral is a dummy variable equal to one if the loan is secured with collateral and zero otherwise; Covenants is a dummy variable equal to one if the loan is secured with covenants and zero otherwise; Refinancing is an indicator variable equal to one if a loan refinances a previous loan and zero otherwise. Lender and Borrower characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debts over total assets; Fixed assets is the ratio of fixed assets over total assets. Net income is the ratio of net income over total assets. The variables are winsorised at the bottom and top 1% levels. Values in parentheses denote standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Banks	Shadow Banks	Dif. mean	EU	CMA9	Dif. mean
Loan characteristics						
Log(spread)	5.436	5.498	0.061***	5.432	5.482	-0.050
			(3.387)			(-1.654)
Log(size)	5.301	5.556	0.255***	5.285	5.466	-0.181***
			(6.854)			(-3.656)
Log(maturity)	4.128	4.095	-0.032	4.142	3.975	0.167***
			(-1.920)			(6.179)
Collateral	0.502	0.547	0.045**	0.509	0.429	0.080**
			(2.802)			(2.706)
Covenants	0.086	0.098	0.012	0.081	0.147	-0.067**
			(1.239)			(-3.235)
Refinancing	0.637	0.616	-0.021	0.629	0.724	-0.096***
			(-1.302)			(-3.591)
Lender characteristics						
Log(size)	14.154	14.749	0.595***	14.018	15.907	-1.939***
			(5.224)			(-7.739)
Leverage	0.097	0.129	0.032***	0.095	0.116	-0.021*
			(4.367)			(-2.477)
Fixed assets	0.102	0.052	-0.051***	0.108	0.021	0.088***
			(-5.424)			(16.875)
Net income	0.031	0.026	-0.006*	0.029	0.056	-0.027*
			(-1.966)			(-2.431)
Borrower characteristics						
Log(size)	12.659	12.701	0.041	12.683	12.408	0.276*
			(0.631)			(2.139)
Leverage	0.297	0.279	-0.018*	0.292	0.359	-0.067***
			(-2.005)			(-3.342)
Fixed assets	0.635	0.652	0.017*	0.641	0.573	0.068***
			(2.099)			(3.407)
Net income	0.029	0.041	0.012***	0.029	0.037	-0.009
			(3.557)			(-1.802)
Observations	3563	1314	4877	3251	312	3563

Table 3. Differences in the mean of each time step in the implementation of the PSD2. Columns (1) to (3) consider 12 January 2016 as the date of introduction of the PSD2; Columns (4) to (6) consider 13 January 2018 as the deadline for member states to adopt the PSD2. Columns (7) to (9) consider the actual date of PSD2 adoption for each member state included in Table 1. The variables included are defined as follows: Loan characteristics – Log(spread) is the natural logarithm of all-in-drawn spread over LIBOR plus the facility fee; Log(size) is the natural logarithm of the loan facilitated; Log(maturity); Collateral is a dummy variable equal to one if the loan is secured with collateral and zero otherwise; Covenants is a dummy variable equal to one if the loan is secured with covenants and zero otherwise; Refinancing is an indicator variable equal to one if a loan refinances a previous loan and zero otherwise. Lender and borrower characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debts over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets. The variables are winsorised at the bottom and top 1% levels. Values in parentheses denote standard errors. $***$ $p < 0.01$, $**$ $p < 0.05$, $*$ $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pre-Introduction	Post-Introduction	Dif. mean	Pre-Adoption	Post- Adoption	Dif. mean	Pre-Staggered	Post-Staggered	Dif. mean
Loan characteristics									
Log(spread)	5.531	5.396	0.097***	5.483	5.341	0.142***	5.460	5.363	0.097***
			(6.584)			(7.291)			(4.642)
Log(size)	5.385	5.266	0.119**	5.302	5.300	0.002	5.255	5.443	-0.188***
			(2.888)			(0.033)			(-3.671)
Log(maturity)	4.118	4.132	-0.013	4.120	4.144	-0.024	4.132	4.114	0.018
			(-0.695)			(-1.335)			(0.919)
Collateral	0.515	0.497	0.018	0.518	0.469	0.050**	0.493	0.531	-0.039*
			(1.007)			(2.786)			(-1.998)
Covenants	0.098	0.082	0.016	0.110	0.037	0.073***	0.098	0.052	0.045***
			(1.494)			(8.680)			(4.766)
Refinancing	0.562	0.669	-0.107***	0.596	0.721	-0.124***	0.602	0.742	-0.140***
			(-5.976)			(-7.514)			(-7.978)
Lender characteristics									
Log(size)	13.984	14.221	-0.238	14.107	14.242	-0.135	14.085	14.345	-0.269*
			(-1.810)			(-1.158)			(-2.074)
Leverage	0.106	0.093	0.013*	0.104	0.083	0.021***	0.103	0.079	0.024***
			(2.128)			(3.468)			(3.879)
Fixed assets	0.129	0.092	0.037***	0.109	0.090	0.019*	0.108	0.084	0.024*
			(3.596)			(2.144)			(2.579)
Net income	0.018	0.037	-0.019***	0.025	0.042	-0.017***	0.027	0.042	-0.015**
			(-6.122)			(-3.945)			(-2.996)

Borrower characteristics									
Log(size)	12.606	12.769	-0.163*	12.685	12.408	0.277*	12.624	12.768	-0.145
			(-2.151)			(2.139)			(-1.828)
Leverage	0.316	0.258	0.058***	0.292	0.359	-0.067***	0.310	0.257	0.053***
			(5.890)			(-3.344)			(4.915)
Fixed assets	0.649	0.605	0.044***	0.641	0.573	0.068***	0.649	0.591	0.058***
			(4.634)			(3.411)			(5.471)
Net income	0.025	0.039	-0.015***	0.029	0.037	-0.009	0.029	0.032	-0.003
			(-4.643)			(-1.807)			(-1.030)
Observations	1066	2497	3563	2400	1163	3563	2686	877	3563

Table 4. The main results of equation 1 related to the event study analysis that capture the impact of implementation of the PSD2 on banks. Columns (1) to (6) report the results for the regression specification that includes the time variable dummy for the introduction of the PSD2, which takes value one after 12 January 2016 and zero otherwise. Columns (7) to (12) report the results for the regression specification that includes the time variable dummy for the adoption of the PSD2, which takes value one after 13 January 2018 and zero otherwise. The lag variables are defined as follows. Loan characteristics – Log(spread) is the natural logarithm of all-in-drawn spread over LIBOR plus the facility fee; Log(size) is the natural logarithm of the loan facilitated; Log(maturity); Collateral is a dummy variable equal to one if the loan is secured with collateral and zero otherwise; Covenants is a dummy variable equal to one if the loan is secured with covenants and zero otherwise; Refinancing is an indicator variable equal to one if a loan refinances a previous loan and zero otherwise. Borrower characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debts over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets. Bank characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debts over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets; Log(loans) is the natural logarithm of bank total loans; Deposit is the ratio of deposits over bank total assets; LLP is the ratio of total loan loss provisions over bank total assets; Tier 1is the ratio of Tier 1 capital over risk-weighted assets. The models include specifications for bank*firm fixed effects, bank and firm quarter fixed effects and clustered bank standard errors. Values in parentheses denote standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Ln(spread)	Ln(spread)	Ln(spread)	Collateral	Collateral	Collateral	Ln(spread)	Ln(spread)	Log(spread)	Collateral	Collateral	Collateral
Introduction PSD2	-0.0528***	-0.0767***	-0.0362**	0.0052	0.0024	0.0197						
	(-3.9318)	(-4.2966)	(-2.6170)	(0.7278)	(0.3353)	(1.3111)						
Adoption PSD2							0.0453***	0.055***	0.0438**	0.0177***	0.0067	0.0194**
							(3.3931)	(3.8334)	(2.1442)	(3.0506)	(1.3988)	(2.6606)
Observations	3,382	3,131	1,336	3,382	3,131	1,336	3,382	3,131	1,336	3,382	3,131	1,336
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
Firm Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Bank*Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R-Adj.	0.933	0.939	0.937	0.968	0.967	0.976	0.933	0.939	0.937	0.968	0.967	0.976

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 5. The specification of equation 1 related to the staggered DiD for decomposing the staggered effects in the different treatment periods and cohorts. Columns (1) to (6) report the results for the staggered treatment adoption regression specification that includes time dummy variables for each of the exact dates of the adoption of the PSD2 in the EU member states (and the UK). Columns (4) to (12) report the regression specification results, including the decomposition effect for the early, deadline and late treatments on the overall treated sample as specified in Table 1. The lag variables are defined as follows. Loan characteristics – Log(spread) is the natural logarithm of all-in-drawn spread over LIBOR plus the facility fee; Log(size) is the natural logarithm of the loan facilitated; Log(maturity); Collateral is a dummy variable equal to one if the loan is secured with collateral and zero otherwise; Covenants is a dummy variable equal to one if the loan is secured with covenants and zero otherwise; Refinancing is an indicator variable equal to one if a loan refinances a previous loan and zero otherwise; Borrower characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debts over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets. Bank characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debts over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets; Log(loans) is the natural logarithm of bank total loans; Deposit is the ratio of total deposits over bank total assets; LLP is the ratio of total loan loss provisions over bank total assets; Tier 1 is the ratio of Tier 1 capital over risk-weighted assets. The models include specifications for bank*firm fixed effects, bank and firm quarter fixed effects and clustered bank standard errors. Values in parentheses denote standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Ln(spread)	Ln(spread)	Ln(spread)	Collateral	Collateral	Collateral	Ln(spread)	Ln(spread)	Log(spread)	Collateral	Collateral	Collateral
Staggered	0.0513***	0.0485***	0.0471**	0.0115*	0.0053	0.0135**						
	(4.1609)	(3.8562)	(2.1925)	(1.7577)	(1.1326)	(2.1353)						
Early T.*Date Adoption							0.0375	0.0449	0.0500	0.0083	0.0111	0.0150
* Treatment							(1.0738)	(1.1138)	(0.7507)	(0.9519)	(0.4200)	(0.3927)
Deadline T.*Date Adoption*							0.1352***	0.1354***	0.1493**	0.0168*	-0.0011	0.0313
Treatment							(4.4224)	(3.0668)	(2.1567)	(1.8233)	(-0.0376)	(0.7899)
Late T.*Date Adoption							0.0379***	0.0335*	0.0323	0.0112*	0.0053	0.0107
* Treatment							(3.6233)	(1.7641)	(1.2257)	(1.8126)	(0.4251)	(0.7103)
Observations	3,382	3,131	1,336	3,382	3,131	1,336	3,382	3,131	1,336	3,382	3,131	1,336
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
Firm Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Bank*Firm Fes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Quarter Fes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Quarter Fes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R-Adj.	0.933	0.939	0.937	0.933	0.942	0.939	0.968	0.967	0.976	0.968	0.968	0.977

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6. The results of the decomposition of the staggered estimations for the Doubly robust DiD, Regression-based DiD, and IPW DiD. The variables of interest are: Log(spread) is the natural logarithm of all-in-drawn spread over LIBOR plus the facility fee and collateral is a dummy variable equal to one if the loan is secured with collateral and zero otherwise. For all specifications of the models that include a loan, bank, and borrower are reported and the coefficients of interest are the wild-bootstrap cluster standard errors at the bank level and the confidence interval at 95%.

Variables	(1) Ln(Spread)	(2) Ln(Spread)	(3) Ln(Spread)	(4) Collateral	(5) Collateral	(6) Collateral
Doubly robust DiD:						
ATT - Early Treat	0.0937	0.2912	0.0115	0.1100	0.1134	-0.2806
	(0.047)	(0.201)	(0.052)	(0.059)	(0.102)	(0.324)
	[0.001, 0.187]	[-0.103, 0.686]	[-0.090, 0.113]	[-0.005, 0.225]	[-0.087, 0.314]	[-0.915, 0.354]
ATT - Deadline Treat	-0.1339	0.0585	0.0037	0.0832	0.1717	0.2074
	(0.051)	(0.105)	(0.097)	(0.063)	(0.090)	(0.095)
	[-0.233, -0.035]	[-0.147, 0.264]	[-0.187, 0.195]	[-0.040, 0.206]	[-0.004, 0.348]	[0.022, 0.393]
ATT - Late Treat	0.0991	-0.0347	-0.0807	-0.0716	-0.2634	-0.3530
	(0.049)	(0.058)	(0.072)	(0.057)	(0.232)	(0.224)
	[0.003, 0.196]	[-0.149, 0.079]	[-0.221, 0.060]	[-0.183, 0.040]	[-0.718, 0.191]	[-0.791, 0.085]
Regression-based DiD:						
ATT - Early Treat	0.0774	0.0473	0.0219	0.1407	0.2206	0.2157
	(0.070)	(0.078)	(0.079)	(0.058)	(0.096)	(0.097)
	[-0.060, 0.214]	[-0.106, 0.201]	[-0.132, 0.176]	[0.027, 0.254]	[0.032, 0.409]	[0.026, 0.406]
ATT - Deadline Treat	-0.1130	-0.0629	-0.0865	-0.0174	0.1848	0.2026
	(0.076)	(0.119)	(0.122)	(0.062)	(0.215)	(0.188)
	[-0.262, 0.036]	[-0.296, 0.170]	[-0.326, 0.153]	[-0.139, 0.104]	[-0.236, 0.606]	[-0.166, 0.571]
ATT - Late Treat	0.0263	0.0710	0.0482	-0.0716	-0.0637	-0.1333
	(0.060)	(0.091)	(0.096)	(0.056)	(0.066)	(0.078)
	[-0.091, 0.144]	[-0.107, 0.249]	[-0.141, 0.237]	[-0.181, 0.038]	[-0.194, 0.066]	[-0.286, 0.019]
IPW DiD:						
ATT - Early Treat	1.1088	-0.6728	-0.0818	0.2076	0.0598	0.0865
	(0.854)	(1.586)	(1.441)	(0.079)	(0.132)	(0.106)
	[-0.565, 2.783]	[-3.782, 2.436]	[-2.906, 2.743]	[0.052, 0.363]	[-0.198, 0.318]	[-0.121, 0.294]
ATT - Deadline Treat	0.4795	-0.3033	-2.1495	0.0087	-0.0490	-0.2685
	(0.873)	(1.347)	(2.267)	(0.116)	(0.171)	(0.206)
	[-1.232, 2.191]	[-2.942, 2.336]	[-6.594, 2.295]	[-0.218, 0.236]	[-0.384, 0.286]	[-0.673, 0.136]
ATT - Late Treat	-0.9142	1.6657	0.2764	-0.1387	0.3234	0.2078
	(0.693)	(1.522)	(1.679)	(0.090)	(0.127)	(0.127)
	[-2.273, 0.445]	[-1.317, 4.648]	[-3.014, 3.567]	[-0.316, 0.039]	[0.075, 0.572]	[-0.041, 0.456]
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	No	No	Yes	No	No	Yes
Bank Controls	No	Yes	Yes	No	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank
Observations	3467	1,993	1,880	3467	1,993	1,880

Table 7. The results of equation 2 for the DiD estimation specification indicate that the treatment group includes banks that have adopted an API and owes a TTP, whereas the control group consists of banks without an API. Columns (1) to (6) report the results for the regression specification that includes the interaction with the time variable dummy for the introduction of the PSD2, which takes value one after 12 January 2016 and zero otherwise. Columns (6) to (12) report the results for the regression specification that includes the interaction with the time variable dummy for the adoption of the PSD2, which takes value one after 13 January 2018 and zero otherwise. Loan characteristics – Log(spread) is the natural logarithm of all-in-drawn spread over LIBOR plus the facility fee; Log(size) is the natural logarithm of the loan facilitated; Log(maturity); Collateral is a dummy variable equal to one if the loan is secured with collateral and zero otherwise; Covenants is a dummy variable equal to one if the loan is secured with covenants and zero otherwise; Refinancing is an indicator variable equal to one if a loan refinances a previous loan and zero otherwise. Lender and Borrower characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debt over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets. The models include specifications for bank, firm and quarter fixed effects and clustered bank standard errors. Values in parentheses denote standard errors. $*** p < 0.01$, $** p < 0.05$, $* p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Ln(spread)	Ln(spread)	Ln(spread)	Collateral	Collateral	Collateral	Ln(spread)	Ln(spread)	Log(spread)	Collateral	Collateral	Collateral
Introduction PSD2*API	-0.0301**	-0.0417***	-0.0098	0.0055	0.0027	0.0143						
	(-2.5367)	(-2.7602)	(-1.1744)	(0.7594)	(0.4145)	(1.4163)						
Adoption PSD2*API							0.0244**	0.0316**	0.0378*	0.0097**	0.0037	0.0177***
							(2.0257)	(2.3692)	(2.0290)	(2.3291)	(0.9946)	(2.8928)
Observations	3,361	3,112	1,319	3,361	3,112	1,319	3,361	3,112	1,319	3,361	3,112	1,319
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
Firm Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R-Adj.	0.933	0.939	0.936	0.969	0.968	0.980	0.933	0.939	0.936	0.969	0.968	0.980

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8. The results of the DiD regressions on the UK bank market presented in equation 2, where the treatment variable is CMA9, which takes value one if the loan is made by the nine largest UK banks. Columns (1) to (6) report the estimation of the model that includes the dummy interaction term OBIE, which takes value one after 19 September 2017 and zero otherwise, and CMA9. Columns (7) to (12) report the results for the regression specification that includes the time variable dummy for the adoption of the PSD2, which takes value one after 13 January 2018 and zero otherwise. The lag variables are defined as follows. Loan characteristics – Log(spread) is the natural logarithm of all-in-drawn spread over LIBOR plus the facility fee; Log(size) is the natural logarithm of the loan facilitated; Log(maturity); Collateral is a dummy variable equal to one if the loan is secured with collateral and zero otherwise; Covenants is a dummy variable equal to one if the loan is secured with covenants and zero otherwise; Refinancing is an indicator variable equal to one if a loan refinances a previous loan and zero otherwise. Borrower characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debts over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets. Bank characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debts over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets; Log(loans) is the natural logarithm of bank total loans; Deposit is the ratio of total deposits over bank total assets; LLP is the ratio of total loan loss provisions over bank total assets. Tier 1 is the ratio of Tier 1 capital over risk-weighted assets. The models include specifications for bank, firm and quarter fixed effects and clustered bank standard errors. Values in parentheses denote standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1) Ln(spread)	(2) Ln(spread)	(3) Ln(spread)	(4) Collateral	(5) Collateral	(6) Collateral	(7) Ln(spread)	(8) Ln(spread)	(9) Log(spread)	(10) Collateral	(11) Collateral	(12) Collateral
OBIE*CMA9	0.0303	0.0427	0.1338**	0.0210	0.0025	0.0750*						
	(1.6449)	(1.2662)	(2.4466)	(1.5698)	(0.1976)	(1.7945)						
Adoption*CMA9							0.0277	0.0520*	0.1214**	0.0228	0.0174	0.0728
							(1.6411)	(1.8664)	(2.0511)	(1.5716)	(1.3704)	(1.6467)
Observations	3,382	3,131	1,336	3,382	3,131	1,336	3,382	3,131	1,336	3,382	3,131	1,336
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
Firm Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R-Adj.	0.929	0.928	0.939	0.956	0.962	0.970	0.929	0.928	0.939	0.956	0.962	0.969

Robust t-statistics in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9. The results of equation 1 for the specification that considers the subsample of shadow banks. Columns (1) to (6) report the results for the regression specification that includes the time variable dummy for the introduction of the PSD2, which takes value one after 12 January 2016 and zero otherwise. Columns (6) to (12) report the results for the regression specification that includes the time variable dummy for the adoption of the PSD2, which takes value one after 13 January 2018 and zero otherwise. Columns (7) to (9) report the results for the staggered treatment adoption regression specification that includes time dummy variables for each of the exact dates of adoption of the PSD2 in the EU member states (and the UK). The lag variables are defined as follows. Loan characteristics – Log(spread) is the natural logarithm of all-in-drawn spread over LIBOR plus the facility fee; Log(size) is the natural logarithm of the loan facilitated; Log(maturity); Collateral is a dummy variable equal to one if the loan is secured with collateral and zero otherwise; Covenants is a dummy variable equal to one if the loan is secured with covenants and zero otherwise; Refinancing is an indicator variable equal to one if a loan refinances a previous loan and zero otherwise. Lender and Borrower characteristics – Log(size) is the natural logarithm of total assets; Leverage is the ratio of total debt over total assets; Fixed assets is the ratio of fixed assets over total assets; Net income is the ratio of net income over total assets. The models include specifications for bank, firm and quarter fixed effects and clustered bank standard errors. Values in parentheses denote standard errors. ∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, ∗ $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Ln(spread)	Ln(spread)	Ln(spread)	Collateral	Collateral	Collateral	Ln(spread)	Ln(spread)	Log(spread)	Collateral	Collateral	Collateral
Introduction PSD2	0.0064	0.0205	0.0737	0.0145	0.0156	-0.0045						
	(0.2436)	(0.6886)	(1.2062)	(1.2812)	(1.4170)	(-0.5216)						
Adoption PSD2							0.0614***	0.0566**	0.1047*	0.0328*	0.0158	0.0112
							(2.7093)	(2.3735)	(1.7683)	(1.9239)	(1.4920)	(0.9461)
Observations	1,167	1,076	391	1,167	1,076	391	1,167	1,076	391	1,167	1,076	391
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	-	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes
Firm Controls	-	Yes	-	-	Yes	-	-	Yes	-	-	Yes	-
Bank FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R-Adj.	0.936	0.931	0.919	0.968	0.980	0.951	0.939	0.932	0.919	0.968	0.980	0.951

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 1. Plots of the coefficients with the confidence interval at 95% for the saturated models with loan, borrowers and bank controls of equation 1 for the different cohorts defined in panel 1 and imposing 0 on the relative time of the introduction of the PSD2 in 2016. Panel (A) reports the coefficients for the year variation of fixed effects; Panel (B) reports the coefficients for the half-year variation of fixed effects; Panel (C) reports the coefficients for the quarterly variation of fixed effects.

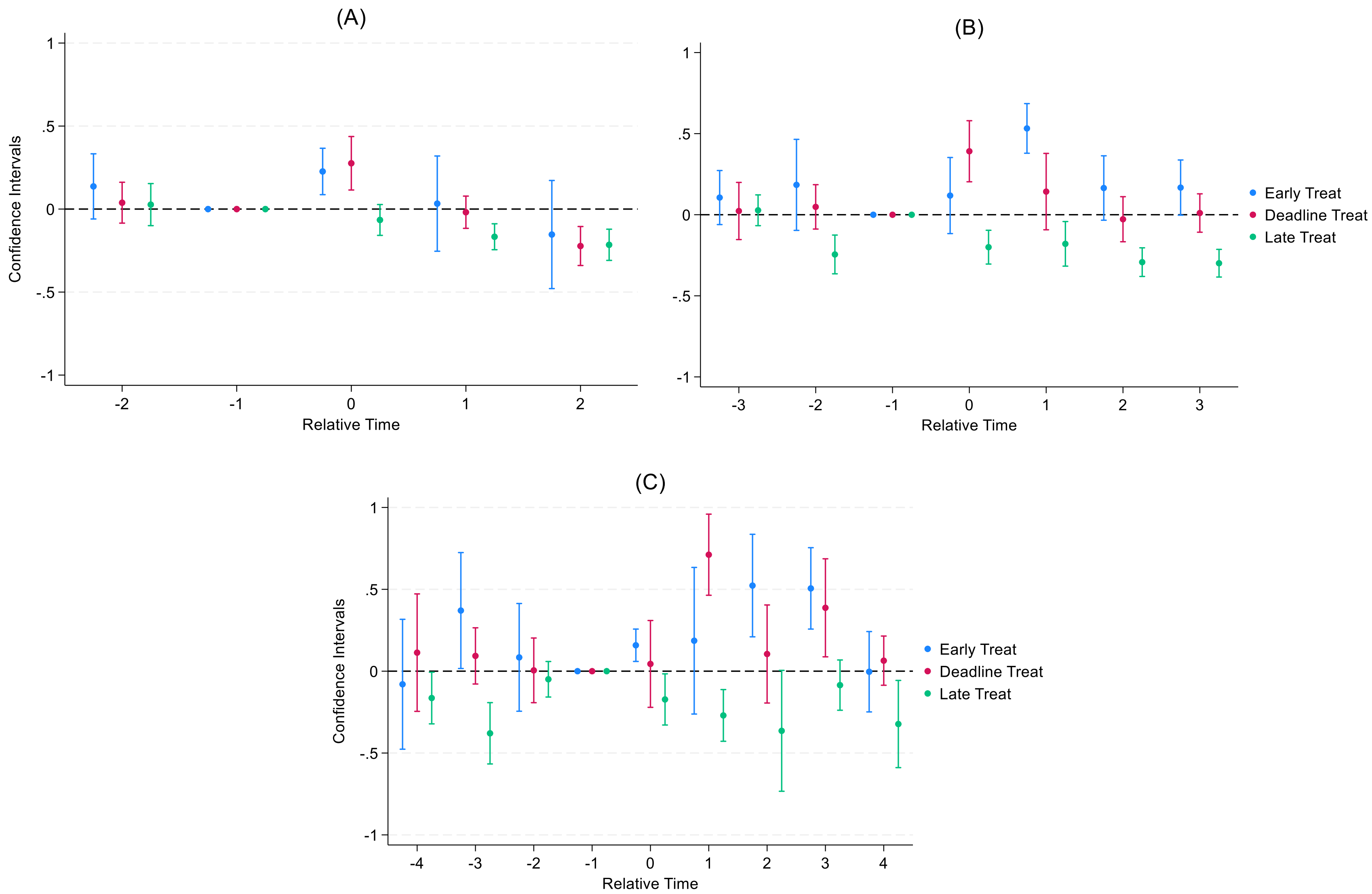
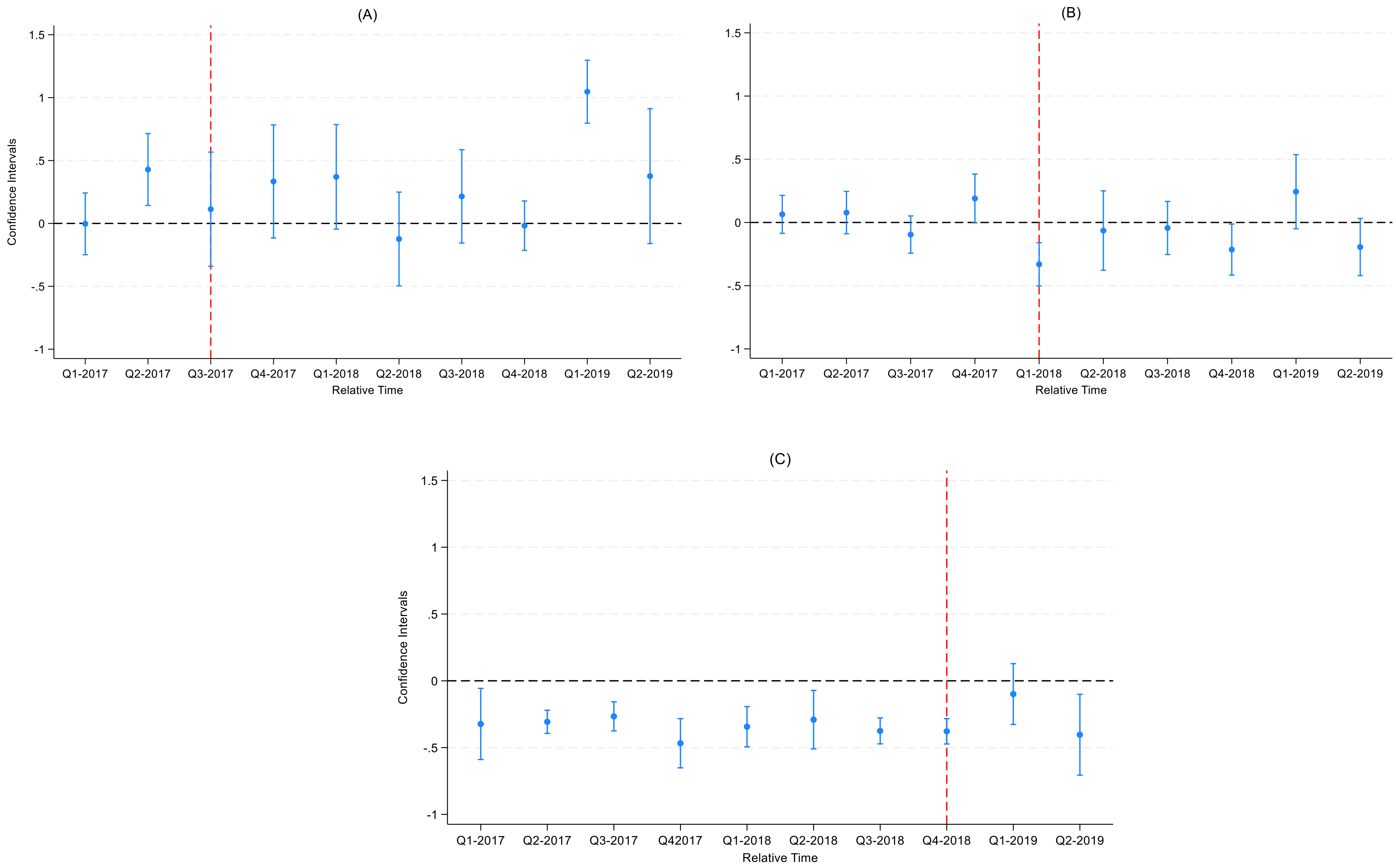


Figure 2. Plots of the coefficients of quality-year fixed effects with the confidence interval at 95% for the saturated models with loan, borrowers and banks controls of equation 1 for the different cohorts defined in panel 1 where the line indicates the quarter of the adoption of the PSD2. In detail, panel (A) report the dynamics of early treatment; Panel (B) the deadline treatment; Panel (C) the late treatment.



Appendix 1. Variables included in the paper with descriptions and data sources.

Laon Characteristics	Description	Source
Log(spread)	The natural logarithm of all-in-drawn spread over LIBOR plus the facility fee.	DealScan
Log(size)	The natural logarithm of the loan facilitated.	DealScan
Log(maturity)	The number of calendar months between the loan origination date and the loan maturity date.	DealScan
Collateral	A dummy variable equal to one if the loan is secured with collateral and zero otherwise.	DealScan
Covenants	A dummy variable equal to one if the loan is secured with covenants and zero otherwise.	DealScan
Refinancing	An indicator variable equal to one if a loan refinances a previous loan and zero otherwise.	DealScan
Lender Characteristics		
Log(size)	Natural logarithm of total assets.	Orbis
Leverage	Total debts over total assets.	Orbis
Fixed assets	Fixed assets over total assets.	Orbis
Net income	Net income over total assets.	Orbis
Bank Characteristics		
Log(loans)	Natural logarithm of bank total loans.	BankFocus
Deposit	Total deposits over bank total assets.	BankFocus
LLP	Total loan loss provisions over bank total assets.	BankFocus
Tier 1	Tier 1 capital over risk-weighted assets.	BankFocus
Borrower Characteristics		
Log(size)	Natural logarithm of total assets.	Orbis
Leverage	Total debts over total assets.	Orbis
Fixed assets	Fixed assets over total assets.	Orbis
Net income	Net income over total assets.	Orbis

Come Together: Payment Systems and System Risks

Nico Lauridsen*

Abstract

This paper examines how the crucial role of payment statistics relevant institutions (PSRIs) was related to the characteristics of banks during the pandemic. It investigates the dynamics of propagation of systemic risk and employs an empirical cross-section analysis of 101 systemic institutions, examining two dimensions of the financial contagion effect. First, it shows that PSRIs amplify the idiosyncratic characteristics of banks that usually affect systemic risk, considering the overall impact of COVID-19 on bank market performance and liquidity structure. Second, the paper analyses the commercial and market bank relationships as one of the channels of transmission of economic distress in the pandemic. It shows that PSRIs could be a valuable additional measure of the centrality of systemic risk. Furthermore, the results show that a better capital structure and government intervention can avoid creating significant liquidity shocks in the interbank market which could trigger domino effects in the banking sector.

Keywords: payment systems, systemic risk, COVID-19, credit trade, supply chain network

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1. Introduction

This paper investigates the relationship between payment systems and systemic risk. These two fundamental components of the financial sector have only recently been studied together. The function of payment systems is to determine the liquidity structure of the financial sector which is implicitly allocated through interbank agreements to settle payments on a net basis (Kahn and Roberds, 2009). However, net settlement of large-value interbank payments has faced criticism for its vulnerability to systemic risk. Systemic risk, which is broadly defined as the risk of a single bank failing to settle triggering multiple settlement failures, has prompted regulatory scrutiny. While actual chains of failures are rare, occurrences of 'near misses' have led to significant regulatory concerns. This shows that the design of payment systems is crucial to systemic risk (Tirole and Rochet, 1996; Allen & Gale, 2000; Parlour et al., 2022). The need to investigate the mechanism behind the interaction between payment systems and systemic risk that can generate contagious financial dynamics and trigger financial instability leads to this paper's research question: can payment systems propagate economic shocks into systemic risk?

This paper differs from previous literature on systemic risk, exploiting the recent pandemic as an empirical context to investigate this research question and test relevant hypotheses. The economic crisis triggered by COVID-19 stands apart from previous downturns such as the global financial crisis of 2007-2009, which resulted from prolonged financial imbalances. The pandemic marked a sudden and severe global economic slowdown. The COVID-19 crisis was unparalleled in terms of its cause, scope and severity (Ding et al., 2021). These distinctions underline the need for research into the factors influencing responses to the unique challenges posed by COVID-19 to countries, firms and individuals (Didier et al., 2021). Indeed, the economic distress caused by the pandemic created a unique opportunity to study how liquidity shocks affect the financial sector and the influence of payment systems on systemic risk. This empirical setting allows a deeper understanding of the propagation of shocks from the real economy to the financial sector and the role of payment systems in transmitting the effects (Berger and Demirgüç-Kunt, 2021).

Specifically, this paper studies how the role of payment statistics relevant institutions (PSRIs) was related to the idiosyncratic characteristics of banks during the pandemic.[8] To contextualise this relationship between payment systems and systemic risk in the COVID-19 period, trade credit theory on the liquidity interdependence structure in supply chain networks is used (Ferris et al., 1981; Osadchiy et al., 2016; Campello and Gao, 2017). Indeed, the interconnection of supply chains was one of the main channels for the propagation of economic distress during the pandemic (Ding et al., 2021). The paper merges the three elements of PSRIs, systemic risk and market and commercial banks relationships, making valuable contributions to different streams of literature. Empirical evidence shows that PSRIs amplify the idiosyncratic characteristics of banks that usually affect systemic risk, such as their size and loan credit exposure (Demirgüç-Kunt and Huizinga, 2013; Jorion, 2009; Acharya and Thakor, 2016; Brunnermeier et al., 2020; Mayordomo et al., 2014; Berger et al., 2023; Anginer et al., 2014; Altunbas et al., 2017). However, in the case of the pandemic, liquid assets and market funding played important roles in mitigating the negative effect of the freeze of supply chains (Borri and Di Giorgio, 2021; Igan et al., 2023). This underlying combination of a good capital structure and government helped avoid creating a significant liquidity shock in the interbank market that could have generated a domino effect in the financial sector (Roukny et al., 2018; Castiglionesi and Eboli, 2018; Denbee et al., 2021). In the end, analysis of market and commercial banks relationships shows that PSRIs could be a valuable additional measure of centrality of systemic risk that considers interconnections among financial intermediaries from a more managerial perspective (Osadchiy et al., 2016; Campello and Gao, 2017).

[8] PSRIs are payment systems which have the potential to trigger or transmit systemic disruptions. These include, among other things, systems that are the sole payment system in a jurisdiction or the principal system in terms of the aggregate value of payments, and systems that mainly handle time-critical high-value payments or settle payments used to effect settlement in other FMIs (BIS glossary).

The empirical cross-section analysis in this paper is divided in three different levels, and it is based on an ECB database, which was used to identify which systemic institutions have a PSRI. The first part looks at the overall effect of the pandemic on the performance of the banking market and shows that having a PSRI is an important determinant of systemic risk exposure. The second part of the analysis goes deeper and studies which individual characteristics of a bank's PSRI drive the systemic risk. The last part extends the study by including the third analytical dimension of supply chain networks and looking at their effect in relation to PSRIs and systematic risk replication in the first part of the study. Furthermore, future extensions of the paper should consider testing the hypothesis using a panel setting with a difference and differences set-up to make the result from cross-section analysis more robust.

The structure of the paper is as follows. Section 2 is a review of two streams of literature: payment systems and systemic risk, and credit trade. Section 3 develops hypotheses based on the literature review. Section 4 describes the empirical setting of the pandemic in detail. Section 5 explains the methodology and describes the data. Section 6 shows the impact of COVID-19 on bank market performance, bank characteristics, systemic risk and the market and commercial banks relationships effect. Section 7 concludes.

2. Literature review and hypothesis development

2.1 Related literature

This paper makes a valuable contribution by exploring the intersection of two separate streams of literature. The first stream considers a critical aspect of the role of payment systems in propagating liquidity shock effects and thus positively contributing to overall systemic risk. The second focuses on trade credit theory and the financial impact of the supply chain network. By bringing these two streams together, the paper sheds light on the complex dynamics of systemic risk. Furthermore, it provides valuable insights leading to a better understanding of the effects of economic shocks in the banking sector, such as the pandemic.

The extensive literature on systemic risk explores various determinants of how banks contribute to systemic risk. Previous studies have demonstrated that single characteristics of banks, such as size, financial leverage, the extent of diversification activities, holdings of financial derivatives, public bailouts and other external factors, may impact the level of systemic risk of large financial institutions (O'Hara and Shaw, 1990; Demsetz and Strahan, 1997; Penas and Unal, 2004; Demirgüç-Kunt and Huizinga, 2013; Jorion, 2009; Acharya and Thakor, 2016; Brunnermeier et al., 2020; Mayordomo et al., 2014; Berger et al., 2023; Anginer et al., 2014). However, only a limited number of studies investigate the relationship between payment systems and systemic risk (Kahn and Roberds, 2009). The ability of banks to create liquidity off the balance sheet and deposits by transforming illiquid assets into liquid liabilities implies an important risk (Bryant, 1980; Diamond and Dybvig, 1982; Kashyap et al., 2002). This ability to create liquidity is associated with the size of the bank and its related systemic importance (Barger and Bouwman, 2009). Indeed, this is a crucial determinant of policy regulation of systemic risk from both a micro-prudential perspective on optimal capital structure and a macro-prudential one on financial stability (Berger et al., 2016). The optimal capital structure of a bank is determined by a trade-off between regulatory capital requirements to mitigate risk exposure and the use of debt leverage in the liquidity creation process (Acharya and Thakor, 2016). Indeed, undercapitalisation of the financial sector and other characteristics such as leverage, size, maturity mismatch and asset prices are crucial elements contributing to systemic risk (Acharya et al., 2016; Adrian and Brunnermeier, 2016). A different perspective on systemic risk comes from the dynamics of financial contagion and its relationship with payment system infrastructure. A channel for the diffusion of liquidity risk and possible domino effects is the interbank market (Rochet and Tirole, 1996; Allen and Gale, 2000).

Concurrently, the design of payment systems can make better use of information that positively affects credit quality and reasonable collateral and deposit requirements, and in turn reduces systemic risk (Rochet and Tirole, 1996, b). On the one hand, part of this effect is associated with the internal banking market diffusing liquidity risk. This can be avoided by implementing settlement of bank transfers and better use of liquid collateral (Allen et al., 2012). On the other, the interbank market and the repayment structure continue to play crucial roles in driving interconnection in the financial system and contagious effects in the case of a liquidity shock (Acemoglu et al., 2015). Recent studies have investigated interbank network liquidity flows and showed that decentralised interbank deposits can mitigate systemic risk (Castiglionesi and Eboli, 2018). Denbee et al. (2021) highlight that individual bank liquidity shocks can be amplified by the interbank market in the payment system. This literature underlines the crucial role of payment systems in determining bank liquidity with possible externality effects (Parlour et al., 2022).

This paper contributes to the systemic risk literature by showing the role of payment systems transmitting the economic effect of liquidity shocks in systemic risk exposure. The results of the empirical analysis provide novel evidence of the mechanism behind the interdependence between the financial system and the real economy and that payment systems represent a crucial channel through which economic shocks can affect bank viability and dampen overall financial stability.

This paper also looks to the literature on trade credit theory, which considers the role of supply chain finance. In particular, it seeks to understand the implications of payment flow dynamics and their reverberations in the banking system. From a theoretical standpoint, this literature discusses the roles of repayment time and cash imbalance problems, which are generally only accurate when specific conditions are met, in particular when a firm finances payments to suppliers by reducing liquid assets, resulting in no bank borrowing, or is a continual borrower using surplus funds to reduce borrowing (Budin et al., 1970; Haley et al., 1973). Furthermore, trade credit theory has shown that trading partners use trade credit to reduce joint exchange costs, employing uncertain delivery times to generate demand for firms to hold inventories of goods and cash and portraying trade credit as a mechanism separating money exchange from uncertainties in goods exchange, thus enabling more efficient management of cash flows (Ferris et al., 1981). Seminal empirical evidence on the dynamics of trade credit was presented by Petersen and Rajan (1997), who showed that small firms tend to rely more on trade credit when access to credit from financial institutions is limited. This result is also consistent with a broader macro perspective. Indeed, additional research reveals that countries with less developed financial markets substitute growth financing with informal credit from suppliers. Trade credit use affects the average size of firms, suggesting challenges for new firms in obtaining trade credit (Fisman and Love, 2003). Recent studies have explored other factors influencing trade credit and examined the implications of social trust in potentially mitigating biases in bank lending practices and how free-rider problems are exacerbated when suppliers offer substitutable products. This leads to reduced willingness to provide trade credit to retailers in the face of higher product substitutability (Wu et al., 2014; Chod et al., 2019). Suppliers extend trade credit to powerful customers to gain a competitive advantage, with payment terms often influenced by customer strength. Weaker suppliers constrained by bank credit may struggle to offer trade credit, impacting their market competitiveness. Firms may prefer trade credit over price reduction to avoid triggering aggressive competitor reactions, and the two strategies may be used complementarily (Fabbri and Menichini, 2010; Fabbri and Klapper, 2016). Other empirical studies have investigated the implications of trade credit theory for banking systems. The availability of good credit information is essential to factor success, underlining how quick access to comprehensive credit information is essential for trade credit (Klapper, 2006). Indeed, trade credit is a secondary choice after other credit options are exhausted. High-growth and liquidity-challenged firms use more supplier credit, probably due to the costliness of extending trade credit beyond early payment discounts (Cunat, 2007). Campello and Gao (2017) study how credit markets respond to customer concentration in bank loans, showing that higher customer concentration is associated with increased interest rates, more restrictive covenants, shorter loan maturities and weaker banking relationships. Firms with larger financially distressed customers face even worse loan terms, indicating heightened credit risk. Another part of this broader literature studies how exogenous shocks can be propagated along the trade credit supply chain. Natural disasters can have a significant impact on suppliers in affected areas, resulting in substantial output losses for customers, particularly when dealing with specific inputs. These output losses can lead to significant reductions in market value and have a cascading impact on other suppliers (Barrot and Sauvagnat, 2016). Adverse credit shocks resulting from natural disasters have approximately twice the impact. Credit shock propagation is more likely to occur in active supply chains, especially when the same analysts assess partners. Industry competition and financial linkages such as trade credit and substantial sales exposure can amplify the effects of shocks in supply chains. The propagation of adverse shocks is particularly strong in the second and third tiers, but less pronounced for favourable shocks (Agca et al., 2021). This propagation effect of supply chain networks will also be reflected in systemic risk. The impact of the economy on industrial and firm sales is mediated by supply networks, while industrial production is closely correlated with economic conditions. This correlation is further intensified by aggregating orders across multiple customers and it influences production decisions over time. These dynamics have important managerial implications related to the cost of capital, and it is crucial to navigate them effectively (Osadchiy et al., 2016).

The contribution of this second stream of literature on trade credit comes from analysis of the effect of the pandemic on the supply chain network. However, most of the papers in the literature on the impact of COVID-19 focus on asset prices and the source of the resilience to such an unexpected shock, with little emphasis on how COVID-19 affects the banking sector. Some exceptions show that the resilience of banks is driven by the support of macroprudential policy and income diversification that sustains performance, while Borri and Di Giorgio (2022) document that Basel III capital requirements contributed to mitigating this negative effect on the financial system (Igan et al., 2023). Unlike other works in the literature, this paper uses the pandemic as an empirical setting to study how the interdependence of supply chain networks of financial intermediaries affects systemic risk. The results show that PSRIs can be interpreted as centrality measures that affect systemic risk and exposure of financial systems to financial distress. Indeed, this study contributes to the literature by showing how they represented a channel of propagation of liquidity risk due to the pandemic.

2.2 **Hypothesis development**

The paper presents a first hypothesis that is grounded in solid theoretical arguments in the payment system and systemic risk literatures. The hypothesis focuses on the implications of a liquidity shock and takes into account two fundamental factors. The first is individual characteristics of banks in the liquidity creation mechanism, while the second is the interdependence between financial intermediaries through payment systems. In detail, payment systems underlie the infrastructure function of liquidity provision behind the individual characteristics of banks by having structural implications for systemic risk (Tirole and Rochet, 1996; Allen and Gale, 2000). The relationship between capital structure and funding strategy affects the efficiency of banks creating liquidity off the balance sheet, impacting systemic risk exposure (Acharya and Thakor, 2016). From the perspective of this literature, payment systems affect systemic risk through the interbank network as one of the most important channels that can be amplified and transmit individual liquidity shocks to the entire banking system (Denbee et al., 2021). Indeed, market liquidity is fundamental in banks' funding strategies that might impinge on systemic risk exposure (Demirgüç-Kunt and Huizinga, 2010). However, on the one hand, capital requirements and deposits continue to play significant roles in mitigating the risk in the liquidity creation mechanism and optimal capital structure, even in moments of financial instability (Adrin and Boyarchenko, 2018). On the other hand, the network structure of the interbank market determines the interconnections of financial institutions that drive systemic risk and possible contagion effects in the case of a liquidity shock (Roukny et al., 2018; Andrieş et al., 2022). In this literature, payment systems are defined as the channel through which banks establish liquidity holding strategies that can lead to a mismatch between deposit and non-deposit income (Altunbas et al., 2017). This theoretical and empirical evidence shows that payment systems affect specific bank risk profiles in funding strategies and liquidity creation mechanisms, determining systemic risk exposures and financial stability threats. The first hypothesis regards the relationship between the payment system and systemic risk. It takes into account various arguments in the literature and factors that contribute to this relationship and aims to provide a better understanding of how payment systems can impact the overall stability of the financial system. Based on these arguments, we postulate the following hypothesis:

H1: Payment systems can transmit liquidity shocks, amplifying systemic risk exposures through idiosyncratic bank characteristics.

The second hypothesis is related to the trade credit literature, which highlights the importance of supply chain interdependence in payment systems and firm liquidity structures. Specifically, the repayment time of trade credit plays a crucial role in determining the exposure to liquidity risk of firms in the supply chain, as is reflected in the credit market (Petersen and Rajan, 1997; Fabbri and Klapper, 2016). In the event of a liquidity shock, the interdependence created by the repayment flow of trade credit becomes a critical channel for the propagation of the economic effect of the shock on supply chains. This financial linkage of supply chains also affects the credit market and banks' risk profiles (Campello and Gao, 2017). Moreover, the interplay between the economy and the financial effects of exogenous shocks is reflected in banks due to the interdependence in the supply chain and credit markets (Osadchiy et al., 2016). This mechanism of contagion effects is reflected in bank credit exposure and in the interbank market as an indirect effect of a liquidity shock (Denbee et al., 2021). This effect on the supply chain could be limited to market and commercial bank relationships, which could emphasize propagation dynamics as an additional interconnection within the market (Acemoglu and Tahbaz-Salehi, 2023). The second hypothesis regarding the impact market and commercial bank relationships is based on a theoretical implication behind their effect on systemic risk.

H2: Banks with extended market and commercial bank relationships are more exposed to systemic risk via the propagation effect of payment systems.

Payment systems are fundamental infrastructure that transmits economic effects to the financial system, highlighting their crucial role in determining firms' financial structures and reflexively entering credit banking. Therefore, payment systems are essential for the smooth functioning of the economy and the financial sector within the dynamics of systemic risk.

3. The empirical setting: the context of the pandemic

COVID-19 caused an unprecedented human and economic crisis worldwide, hammering the real economy and having spillover effects on financial markets. Governments employed shutdown and lockdown measures freezing nonessential economic activities to limit the spread of the virus. The nature of this health crisis was different to other past financial crises (Didier et al., 2021). The World Bank forecast an economic downturn in European GDP of -9.1%. At the same time, the pandemic hit the financial markets with a heterogeneous effect on firms' characteristics (Ding et al., 2021). Indeed, the pandemic represents a unique empirical setting to better understand the causal effect and relationship between payments and systemic risk, by analysing the financial and economic effects of the COVID-19 crisis on the banking sector (Berger and Demirgüç-Kunt, 2021). Corporate distress during the pandemic was created by 'hibernation' of payments generating a ripple effect in the global international trade network, which led to a domino effect on national economies and determined that COVID-19 was a global economic shock (Didier et al., 2021). This was reflected in the financial market forecasting future economic outcomes, which is one of the main channels through which the financial market amplified this primary shock from the real economy (Ramelli and Wagner, 2020). On the financial intermediation side, the liquidity shock created by the pandemic put the banking sector under pressure, but it responded better than in past crises thanks to a better capital structure (Li et al, 2020; Schivardi et al., 2020). However, firm financial structures played a crucial role in transmitting the economic effect of the pandemic and defining firm resilience (Albuquerque et al., 2020; Fehlenbrach et al., 2021). In fact, during the pandemic firms with a higher proportion of cash holdings were more likely to fare better than other firms in terms of stock market performance (Ding et al., 2021). This was also reflected in investors' decisions that tended to reward firms with better credit access during the economic downturn (Acharya et al., 2020).

The pandemic had a significant impact on the global economy, and in particular on the financial intermediation side. The liquidity shock due to the pandemic put pressure on the banking system, but it responded better than in past crises thanks to a better capital structure. However, the delay in payment channels in global supply chains created a liquidity shock, which affected the banking system (Li et al., 2020; Schivardi et al., 2020). The COVID-19 pandemic thus highlighted the crucial role of payment systems in transmitting the liquidity shock to the banking system. Looking at the pandemic from a global perspective, government support came from the national level with heterogeneous interventions to mitigate the social and economic costs, not considering interconnections with the global economy. Indeed, systemic institutions are more exposed to global economic shocks. Despite the challenges, the resilience of banks is driven by the support of macroprudential policy and income diversification, which sustains performance. Moreover, the additional capital requirements in Basel III contributed to mitigating the negative effect on the financial system (Borri and Di Giorgio, 2021; Igan et al., 2022; Dursun-de Neef and Schandlbauer, 2021).

The unusual nature of the exogenous shock caused by the pandemic represents a unique context for empirical research to explore how the transmission of liquidity from the real economy passes to the financial and banking systems. Payment systems play a crucial role in understanding this transmission mechanism, which can have significant implications for financial stability.

4. Methodology and Data

Section 4.1 describes the empirical strategy to analyse first individual bank stock market reactions to the pandemic shock for banks with different risk profiles and market performance, then the effect of systemic risk in relation to bank characteristics and afterwards the market and commercial bank relationships to payment systems. Section 4.2 describes the data set and sources.

4.1. Methodology

The empirical analysis in this paper is divided in two distinct logical blocks. The purpose is to test the previously developed hypotheses on the implications of the COVID-19 pandemic on bank activities, and the propagation effect it had on global supply chains via payment systems. The analysis involves several econometric strategies and variables chosen to provide comprehensive insights into the topic. The first part of the analysis relies on two methodological works – Erkens et al. (2012) and Ding et al. (2021) – to identify the effect of the pandemic on the market performance of the banking system, including risk exposure and profitability during the pandemic. To look at the overall effect on the risk profiles of banks and their market performance we use a cross-sectional regression relating ex-ante bank-specific characteristics in the pre-treatment period to stock market performance during the pandemic. Specifically, Equation 1 describes the econometric strategy:

$$MP_{i,firsthalf2020} = \beta_0 + \beta_1 Payment_{i,precovid} + \beta_2 Characteristics_{i,precovid} +$$

$$+\phi_{i,countrey} + \varepsilon_{i,firsthalf2020,} \quad (1)$$

where i=1,2 … N are banks, *MP* is stock market performance and ε is the error term in our empirical model. For stock market performance during the pandemic the analysis uses several different measures.

On the one hand, looking at the bank risk profile, in line with Erkens et al. (2012) MP captures the stock market performance during the pandemic crisis with the buy-and-hold returns (*BHR*) from 1 January 2020 to 30 June 2020. This measure has the advantage of capturing the expected return to an investor if she/he bought the bank stock on the first day of January 2020 and held it until the last day of June. Second, bank stock price volatility over the same time period is used to capture the bank stock risk. Third, we use Brown and Engle (2017)'s bank systemic risk measure – *SRISK* – scaled by bank total assets. This measures the expected loss that a bank may incur in the case of a prolonged and generalised economic downturn (Acharya et al., 2016). In contrast with other measures of systemic risk, it allows estimating a bank's contribution to three systemic risk factors: *i)* the probability that a crisis may occur; *ii)* the expected loss that a bank may incur when the aforementioned crisis does occur; *iii)* the negative externalities associated with decreased bank capital adequacy due to the crisis. Moreover, as an additional measure of the bank risk profile, the analysis considers market beta, which is the beta of the market for the period of our sample, and *asset beta,* which is the value of the market beta discount for the leverage from 2019.

On the other hand, analysis of *MP* investigates the impact of COVID-19 on the profitability of banks considering additional independent variables such as the loan market share, which is the ratio of the loans of a single bank in 2020 to the total loans in the sample in 2020. The *deposit market share* is the ratio of the deposits in a single bank in 2020 to the total deposits in the sample in 2020. *ln (Operating revenue)* is the logarithmic transformation of the total operating revenue in € billion in 2019. *ROA* is the return on assets for 2020 and *Tobin Q* is the logarithmic transformation of the book to market value for 2020 (Delis et al., 2016).

To analyse our variable of interest, which is payments related to the vector of bank-specific characteristics, the empirical model takes into account 2019 pre-pandemic values in order to smooth endogeneity. This also allows us to understand how banks fared during the pandemic according to pre-pandemic firm characteristics. The variable of interest *Payment*, related to β_1, is a dummy variable that takes value one if a bank had a PSRI in its business model in 2019 and zero otherwise.

Furthermore, the empirical model includes β_2, which is the vector of bank-specific characteristics to roll out alternative explanations that may affect the relationship under investigation. As said, all the controls refer to the pre-COVID period, 2019, and they include the log of bank total assets to allow for the bank business model, diversification strategies and economies of scale. In fact, there is some evidence that larger banks are more likely to affect financial stability and contribute to the rise of systemic risk in the case of them defaulting (Drehmann and Tarashev, 2013). Also included are: the ratio of bank total loans to total assets to account for bank lending activities and control for the potential impact of bank funding and asset and liability composition (Beltratti and Stulz, 2012; Acharya and Thakor, 2016); *Equity*, calculated as the ratio of bank equity capital to total assets; *Deposits*, measured as the ratio of total bank deposits to total assets; *Tier 1*, defined as the ratio of bank Tier 1 capital to the bank risk-weighted assets; and *Market Funding*, the ratio of short-term market debt to total assets. Finally, to account for bank profitability, also included are *Net-income*, measured as the ratio of bank net income to total assets, and *Asset Quality*, the ratio of bank loan loss provisions (*LLP*) to total assets in line with Bayazitova and Shivdasani (2012), since banks with lower performance and a higher proportion of non-performing loans are more likely to contribute to overall systemic risk. Finally, the empirical model with $\phi_{i,country}$ includes country fixed effects to consider additional macro factors, which could result from government support and cultural differences among banks or country-specific characteristics (Igan et al., 2023).

To further elaborate on the empirical analysis, the focus is on comprehending the effects of the pandemic on the exposure of the banking system to systemic risk. As in the relevant literature, Equation 2 considers *SRISK* to be the primary variable of interest. It measures systemic risk and has previously been defined (Altunbas et al., 2017). The empirical model is as follows:

$$SRISK_{i,f2020} = \beta_0 + \beta_1 Payment_{i,precovid} * Characteristic_{i,precovid} + \beta_2 Controls_{i,precovid} + \\ + \phi_{i,country} + \varepsilon_{i,firsthalf2020}, \qquad (2)$$

where i=1, 2 … N are banks. The equation is constructed to identify the channels that trigger financial transactions. The payment dummy interacts with the individual characteristics of the bank, leaving the remaining variables as controls. First, it interacts with the direct risk variables that can influence systemic risk to avoid possible problems of reverse causality: market beta and asset beta, liquid assets and inter-banking liquidity (Roukny et al., 2018). Second, the overall characteristics used in Equation 1 are analysed as controls to study the heterogeneous effect of the role of *PSRIs* affecting bank activities. The model is completed with fixed effects to account for additional sources of endogeneity.

The last part of the empirical analysis looks at the interrelationships among banks in market and commercial bank relationships to investigate the propagation dynamics that the pandemic shock could have generated within the liquidity structure of the banking system. The structure of this robustness test replicates the previous one using market and commercial bank relationships, first as an alternative measure of centrality in the liquidity market and second to consider the interdependence of banks through their payment systems. The measure is based on the analysis of

FactSet Revere made by Pieaveenan et al. (2020). Equation 3 reports the measure of market and commercial bank relationships, as follows:

$$SCN_{i,t} = Ln(1 + \sum Relationship), \qquad (3)$$

where i is the individual bank and t indicates the relevant time considered in the *SCN* measure based on establishing activated relationships during the pandemic period in the analysis, that is to 30 June 2020. The variable *Relationship* counts the number of supply chain network relationships that each bank established, including with competitors and suppliers and in partnerships of different nature, such as joint ventures and investments. Furthermore, this type of relationship is reciprocal and dual based on the individual supply chain network of the bank. Indeed, we can distinguish between internal ones, which represent all the links in the bank supply chain network, and external ones, if the bank contributes to another supply chain network as an external participant, which can be considered an additional measure of interconnection in the market.

The structure of the analysis allows us to identify the effects of the pandemic on the banking system and understand the impact of the role of payment systems in the propagation of the liquidity shock created by the freezing of the real economy (Didier et al., 2021). However, the effects of the pandemic on the banking system must continue to be studied by looking at the credit dynamics and risk exposures in the medium and long term, which were initially covered by the government support and grant scheme and could have led to mismatched maturity and moral hazard problems (Berger and Demirgüç-Kunt, 2021; Igan et al., 2023; Pagano and Zechner, 2022).

4.2. Description of the data sample

The sample was constructed by collecting information from different sources on bank systemic risk and PSRIs for 101 listed banks located in 12 EU countries during the most severe phase of the pandemic. Stock information was collected from Thomson Reuters Eikon and merged with bank variables on systemic risk exposure from V-Stern Lab and on individual characteristics from BankFocus.[9] The PSRI data were hand-collected from the European Central Bank database as proxies for centrality in the interbank market (Roukny et al., 2018).[10] Indeed, PSRIs are payment system operators entities that are legally responsible for operating a payment system as a crucial infrastructure for the liquidity in the banking system. The data to construct the market and commercial bank relationships were collected from FactSet. This database collects interfirm relationship data from primary public sources such as investor reports, SEC 10-K annual filings, investor presentations and press releases. The database includes both relationships disclosed by the company and reverse relationships which their partners report. A list of the variables with relevant descriptions is provided in Appendix 1.

Table 1 reports the descriptive statistics for the sample relative to the pandemic period and the bank characteristics. The descriptive statistics of the variables also include the robustness check statistics and extensions. Initially, looking at the outcome variables of interest, they show that bank stock prices were decreasing since the *BHR* shows an average value of -0.252 and volatility was about 0.033. Furthermore, looking at the other variables relative to bank risk factors, the descriptive statistics show an increase in overall systemic risk of 0.006 in *SRISK* and a relative increase in the market beta and asset beta of 0.599 and 0.062 respectively. The distribution of the remaining bank characteristics is omegas due to the fact that the sample is composed of significant institutions. However, only 45% of the sample have a *PSRI*.

9 https://vlab.stern.nyu.edu/
10 https://www.ecb.europa.eu/stats/financial_corporations/list_of_financial_institutions/html/index.en.html#psri

These initial findings suggest that the EU banking sector was severely impacted by the COVID-19 pandemic, leading to an increase in systemic risk exposure and in the overall risk profile (Demirguc-Kunt et al., 2021; Borri and Di Giorgio, 2021; Dursun-de Neef and Schandlbauer, 2021).

[INSERT TABLE 1 ABOUT HERE]

5. Results

This section is structured in three levels of analysis that reflect the steps in the previously described methodological approach. The first part examines the impact of the pandemic on bank stock market performance and profitability. The second part investigates how the individual characteristics of banks affected systemic risk during the liquidity shock attributed to the pandemic. Last, the third part explores the relationship between payment systems and the propagation dynamics of the economic effects of the pandemic on the market and commercial bank relationships.

5.1 The impact of COVID-19 on bank market performance

This first part of the analysis investigates the main effect of the pandemic shock on the market performance of banks to understand which channel transmitted the economic distress generated by the lockdown and shutdown policy to contain the health crisis (Albuquerque et al., 2020; Fehlenbrach et al., 2020; Ramelli and Wagner, 2020). The ability of the financial market to reflect the uncertainty and risk exposure in the banking system is crucial to understand the relationships between the liquidity shock created by the 'hibernation' of the economy and the effects on the banking and financial systems (Ding et al., 2021). During the pandemic, blocking of the global supply chain created a consequent freeze of payment flows transmitted to the banking system. This could have led to increased risk exposure of banks to the relentless credit market (Berger and Demirgüç-Kunt, 2021). The liquidity shock created by the pandemic could have been transmitted via PSRIs, as directed infrastructure through which payment flows determine bank credit exposures and systemic importance.

Table 2 reports the cross-sectional regression results highlighting the nexus between bank stock market performance and payment systems in Equation 1. The results of the regressions reported in columns (1) to (5) have been adjusted for control variables, country-fixed effects and clustered robust standard errors. Analysing the market performance measures for banks having a PSRI, the only significant coefficient is for *SRISK* in column (3), which has a statistically significant value of 0.0070 ($p < 0.05$). Furthermore, looking in more detail at the results in columns (3), estimations consistent with the systemic risk provide initial evidence that PSRIs could have played an important role in transmitting the pandemic liquidity shock (Altunbas et al., 2017). On the one hand, bank size (0.0034; $p < 0.05$) and loan loss provisions increase (0.4114; $p < 0.1$) systemic risk exposure. On the other hand, deposit (-0.4114; $p < 0.05$) and Tier 1 capital requirements (-0.0519; $p < 0.1$) mitigate this additional threat to financial stability.

These preliminary findings provide initial support for the first hypothesis on the relationship between payment systems and systemic risk. However, the results need to be better tested for the different channels the literature considers crucial drivers of bank systemic risk and interconnections among financial intermediaries.

[INSERT TABLE 2 ABOUT HERE]

Moving forward in the analysis, Table 3 extends the results of Equation 1 to investigate the role of PSRIs in bank profitability profiles. Considering the significant outcome variables for the different model specifications, payment systems are only relevant for loan market shares, ln (operating revenue) and Tobin Q. Column (1), which reports the results for the model that looks at loan market shares, shows a small and hight significantly coefficient indicating that banks that have a PSRI had a bigger loan portfolio during the pandemic period. At the same time, column (3) shows that this type of bank increased its operating revenue (0.2127; $p < 0.1$). This result could be driven by diversified bank income, including a rise in non-interest sources such as trading, investment banking and fees. While this diversification might enhance overall income stability, its impact on reducing banking risk is unclear (Altunbas et al., 2017). However, non-interest income may amplify risks during financial stress, like that caused by COVID-19. Indeed, the results for Tobin Q in column (5) reveal a significant reduction in book market value (-0.8416; $p < 0.05$). This can be associated with the negative reaction of the financial market to the pandemic.

This part of the preliminary analysis has shown heterogeneous effects of banks' main characteristics and the role of PSRIs during the pandemic. The following analysis goes deeper into the impact of payment systems on systemic risk and idiosyncratic dimensions that could have amplified systemic risk exposure of banks.

[INSERT TABLE 3 ABOUT HERE]

5.2 Bank characteristics and systemic risk

The second part of the analysis focuses on the role of PSRIs in affecting systemic risk, initially investigating the relationship between the market exposure of banks and their liquidity profile. The results of the model to test the first hypothesis are reported in Table 4. Columns (1) to (4) show the estimation of Equation (2) that considers the interaction payment variables, market beta and assets, and the liquidity profile of banks as the variables of interest. On the one hand, columns (1) and (2) present non-statistically significant coefficients, indicating that PSRIs do not impact bank exposure to financial market risk. On the other hand, columns (3) and (4) respectively show that asset liquidity (-0.0008; $p < 0.01$) and interbank liquidity (-0.0001; $p < 0.01$) have a small but significant effect reducing systemic risk exposure during the pandemic shock, underlining that PSRIs are a fundamental component determining the liquidity structure of banks. Unlike the literature that highlights the role of interbank markets as one of the channels driving financial contagion, the results show that in the case of the pandemic the liquidity profile of banks was crucial in preventing the rise of systemic risk (Roukny et al., 2018; Andries et al., 2022). These results further underline the particularity of the COVID-19 crisis (Berger and Demirgüç-Kunt, 2021).

For this reason, we further investigate the previous results by considering how they are associated with other bank-specific characteristics in determining systemic risk exposure.

[INSERT TABLE 4 ABOUT HERE]

Table 5 shows details of the effective role of PSRIs in relation to systemic risk. The results of extensions of the previous estimations of Equation (2) are reported in columns (1) to (8). Starting with the first interaction terms in column (1), they show a high and positive coefficient of size (0.0041; $p < 0.01$), which can be an important determinant of bank risk. Larger institutions may have different incentives to smaller banks due to the 'too-big-to-fail' problem, which might encourage larger institutions to take more risks. This shows that systemic importance is relevant to PSRIs (Demirgüç-Kunt and Huizinga, 2010). It is also consistent with the evidence in column (2) on loan variables (0.0034; $p < 0.05$), which highlights that these institutions also have larger risk credit portfolios. However, this characteristic of payment systems is not reflected in the capital structure, given the non-significant results for deposits in column (5) and for Tier 1 capital requirements in column (8). At the same time, the coefficient in column (6) for the variable related to market funding (-0.0234; $p < 0.01$) indicates a significant reduction in systemic risk. This shows that in the pandemic short-term liquidity played an important role in mitigating the effects of economic distress. Nonetheless, customer deposits contribute to the stability of bank funding, decreasing the likelihood of a rescue. This suggests that during the pandemic having access to alternative sources of short-term liquidity played a crucial role in reducing negative impacts on the economy. On the other hand, relying on short-term marketable securities can increase the risk of economic distress (Demirgüç-Kunt and Huizinga, 2010). Institutions that heavily rely on short-term market funding face an increased risk of liquidity shortage during a crisis, which can make it difficult to renew short-term debt to support assets that are hard to sell. At the same time, columns (3) and (5) respectively report negative impacts on systemic risks of the coefficients of equity (-0.0347; $p < 0.01$) and net income (-0.1454; $p < 0.01$). The effectiveness of reducing banking risk is still being determined, given the unpredictability of non-interest income, especially in times of financial distress. This raises the question of whether diversification is more helpful in managing smaller individual risks or larger systemic shocks. Nevertheless, loan growth remains a significant risk factor that requires careful consideration (Fahlenbrach et al., 2018).

The results in this section are coherent with findings in the theoretical literature that bank financial interdependencies in payment systems affect their contributions to systemic risk (Kahn and Roberds, 2009). Analysis of the effect of bank characteristics during the pandemic shows a crucial role of payment systems in possible propagation dynamics of the liquidity shock, highlighting that PSRIs could be an alternative measure of impact centrality as has been indicated by the previous results. However, according to our estimates, payment systems seem to contribute to systemic risks in the traditional channels that characterise idiosyncratic risk such as size and loan portfolios (Altunbas et al., 2017). This combined with the capitalisation of banks before the pandemic and government-guaranteed schemes helped to limit financial distress and reduce financial stability, mitigating the dynamics of contagion (Borri and Di Giorgio, 2021; Igan et al., 2022; Dursun-de Neef and Schandlbauer, 2021).

[INSERT TABLE 5 ABOUT HERE]

5.3 The Merket and commercial bank relationships effects

In this last section of the paper, the focus shifts to examining the relationship between the market and commercial bank relationships and systemic risk, specifically regarding the role of payment systems in transmitting economic distress due to a liquidity shock. This empirical analysis contributes to the literature on trade credit in the pandemic as it offers a distinct opportunity to explore the dynamics of propagation in the systemic risk exposure of banks and to test the second hypothesis.

Following the empirical and methodological steps in the first part, the analysis reported in Table 6 shows the Equation (1) regression model that highlights the market reaction of banks to market and commercial bank relationships, introducing an interaction term between the payment variable and the measure described in Equation (3) that considers the different types of relationships among financial intermediaries in the interaction to understand the effect of payment systems. This can be interpreted as an alternative centrality measure of financial interdependence between financial intermediaries that exposes banks to contagious dynamics in the case of financial distress or a liquidity shock (Castiglionesi and Eboli, 2018; Roukny et al., 2018). Looking at the results in columns (1) to (5), the interaction term shows a positive and significant coefficient for the systemic risk variable *SRISK Ratio* (0.0009; $p < 0.01$), supporting the second hypothesis that the market and commercial bank relationships can play an import role in the contagious dynamics of a liquidity shock such as the pandemic. However, moving to the results on the external relationship in column (9), there is an effect of the market beta variable (-0.0246; $p < 0.1$) that could be linked to the hedging strategies of banks to reduce their market exposure during the pandemic shock. This evidence is coherent with the pandemic literature according to which a frozen supply chain is one of the main channels of economic distress (Dien et al., 2021; Didier et al., 2021). At the same time, these results contribute to the trade credit literature, showing that the supply chain network relationship also matters to the systemic risk of transmitting economic distress and creating a liquidity shock (Osadchiy et al., 2016; Campello and Gao, 2017).

[INSERT TABLE 6 ABOUT HERE]

The next part of this analysis investigates in greater depth the role of payment systems in market and commercial bank relationships and the systemic risks involved. This time, based on Equation (2), the internal and external measures of market and commercial bank relationships are decomposed into partnerships of various natures between suppliers, competitors and customers to better understand which types of interaction among financial intermediaries drive the effect on systemic risks. Table 7 shows how the different natures of market and commercial bank relationships affect systemic risks. On the one hand, column (1) shows a high and positive coefficient for the interaction term (0.0221; $p < 0.01$) in line with previous results that in internal market and commercial bank relationships, suppliers, competitors and customers are the ones that drive interconnections among financial intermediaries that can create contagious effects in moments of financial distress. On the other hand, column (4) shows that among external relationships strategic partnerships have a significant coefficient (0.0134; $p < 0.01$), meaning that they are a crucial channel transmitting the effect of a shock like the pandemic over the entire market and commercial bank relationships, thus affecting systemic risk. The results suggest that the commercial and market bank relationships can impact the trade credit suppliers receive, which can result in financial instability. At the same time, this ripple effect created by the pandemic can be amplified by the partnerships and relations within networks.

[INSERT TABLE 7 ABOUT HERE]

6. Conclusion

This paper has studied the important role of payment systems in systemic risk dynamics during the pandemic shock, with a focus on the financial interdependence of commercial and market bank relationships. Bridging two different parts of the financial intermediary literature, the first part of the study found empirical evidence of the crucial role of payment systems in amplifying the idiosyncratic characteristics of banks that can transmit economic distress to the financial sector (Kahn and Roberds, 2009). This contribution to the systemic risk and financial contagion literature provides valuable insights into the different natures of liquidity shock measures that determine the dynamics of propagation (Allen and Gale, 2000; Altunbas et al., 2017). Indeed, in the case of the pandemic liquidity market funding combined with guarantees of government support for the debt structure of firms and better capitalisation of banks helped to mitigate the potential financial instability of the financial system (Borri and Di Giorgio, 2021; Igan et al., 2023).

The second part went a step forward in investigating the effect on the supply chain network by looking at how payment systems are fundamental components in the relationships among financial intermediaries. The analysis of the pandemic economy 'hibernation' period showed that the infrastructure role of payment systems contributes to understanding the mechanisms behind the types of supply chain network links that affect systemic risk and transmit liquidity shocks that can trigger financial instability (Dien et al., 2021; Didier et al., 2021). Internal and external commercial and market bank relationships interdependence affects exposure to systemic risks in trade credit relationships and strategic partnerships (Osadchiy et al., 2016; Campello and Gao, 2017).

However, the effects of the pandemic still need to be studied, not only as a unique analytical setting but also to better understand the impact in the medium and long terms on the credit and risk exposure of banking systems that can be created by the leverage of guarantee schemes (Berger and

Demirgüç-Kunt, 2021). Indeed, this could generate a moral hazard problem in the credit market leading to liquidity maturity mismatches that cause credit deterioration dynamics (Dursun-de Neef and Schandlbauer, 2021; Pagano and Zechner, 2022).

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Table 1. Descriptive Statistics. This table shows summary statistics of our sample (1 January 2020 to 31 July 2020). We report the number of observations (N), the mean (Mean), the median (Median), the standard deviation (S.D.), the minimum (Min.) and the maximum (Max.) for all the variables used. *BHR* stands for buy-and-hold bank stock returns. *Year Volatility* is stock return volatility. *SRISK* is the measure of systemic risk provided by V-Lab (Stern NYU) calculated as the difference between the book value of debt and the long-run marginal expected shortfall. *Market Beta* is the beta of the market for the period of our sample. *Asset Beta* is the value of the market beta discount for leverage from 2019. *Loan market share* is the ratio of bank total loans to the sum of all the sampled banks' total loans in 2020. *Deposit market share* is the ratio of the bank total deposits to the sum of all the sampled banks' total deposits in 2020. *Operating revenue (ln)* is the logarithmic transformation of total operating revenue in € billion for 2019. *ROA* is the return on assets for 2020; *Tobin Q* is the logarithmic transformation of the book to market value for 2020. *Payment* is a dummy variable that takes value one if a bank has a PSRI and zero otherwise. *Size* is the log of the value of the total assets in € billion in 2019. *Loans* is the ratio of loans to total bank assets in 2019. *Equity* is the ratio of equity to bank total assets in 2019. *Net income* is the ratio of net income to bank total assets in 2019. *Deposits* is the ratio of deposits to bank total assets in 2019. *LLP* is the ratio of loan loss provisions to bank total assets in 2019. *Tier 1* is the ratio of regulatory capital to bank total risk-weighted assets in 2019. *Market funding* is the ratio of short-term market debt to bank total assets in 2019.

Summary statistics

	N	Mean	Median	S.D.	Min	Max
BHR	101	-0.252	-0.233	0.210	-0.769	0.254
Year Volatility	101	0.033	0.031	0.016	0.003	0.105
SRISK Ratio	101	0.006	0.000	0.014	0.000	0.080
Market Beta	101	0.599	0.450	0.610	0.000	1.900
Asset Beta	101	0.062	0.067	0.066	0.000	0.280
Loan Market Share	97	0.010	0.002	0.020	0.000	0.106
Deposit Market Share	95	0.011	0.001	0.021	0.000	0.111
ln(Operating Revenue)	96	6.600	6.370	2.069	0.242	10.75
ROA	97	0.004	0.004	0.014	-0.086	0.062
Tobin Q	91	2.923	2.738	2.028	-0.719	8.263
Payment	101	0.455	0.000	0.500	0.000	1.000
Size	101	16.94	16.94	2.335	10.87	21.39
Loans	101	0.538	0.579	0.203	0.020	0.813
Equity	101	0.102	0.092	0.050	0.033	0.391
Net Income	101	0.008	0.006	0.007	-0.008	0.033
Deposits	101	0.107	0.058	0.150	0.000	0.566
LLP	101	0.004	0.002	0.006	-0.013	0.027
Tier I	93	0.178	0.169	0.045	0.081	0.345
Market funding	100	0.573	0.632	0.211	0.000	0.970

Table 2. This table shows the results of the Equation (1) regression models. The dependent variables are the buy-and-hold stock returns (*BHR*), stock price volatility (*Volatility*), *SRISK*, *Market Beta and Asset Beta*. This last variable is calculated as the difference between the book value of debt and long-run marginal expected shortfall. *Payment* is a dummy variable that takes value one if a bank has a PSRI and zero otherwise. Bank-specific variables: *Size* is the log of the value of total assets in € billion in 2019. *Loans* is the ratio of loans to total bank assets in 2019. equity is the ratio of equity to bank total assets in 2019. *Net income* is the ratio of net income to bank total assets in 2019. *Deposits* is the ratio of deposits to bank total assets in 2019. *LLP* is the ratio of loan loss provisions to bank total assets in 2019. *Tier 1* is the ratio of regulatory capital to bank total risk-weighted assets in 2019. *Market funding* is the ratio of short-term market debt to bank total assets in 2019. All the regressions include country fixed effects. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.001.

Variables	(1) *BHR* *(Jan-Jun 2020)*	(2) *Volatility* *(Jan-Jun 2020)*	(3) *SRISK Ratio* *(Jan-Jun 2020)*	(4) *Beta Market* *(Jan-Jun 2020)*	(5) *Asset Beta* *(Jan-Jun 2020)*
Payment	-0.0043	0.0025	0.0070**	0.0127	0.1662
	(-0.3612)	(0.7703)	(2.0112)	(0.4321)	(0.7198)
$Size_{2019}$	0.0009	-0.0017	0.0034**	0.0162***	0.1436***
	(0.3578)	(-1.6459)	(2.5896)	(3.1693)	(3.2505)
$Loans_{pre\text{-}Covid}$	-0.0189	-0.0012	-0.0039	0.0515	0.4700
	(-0.7555)	(-0.1564)	(-0.4032)	(1.2593)	(1.2588)
$Equity_{pre\text{-}Covid}$	0.1649	-0.1037	-0.0163	0.4039*	-1.0699
	(1.4730)	(-1.4347)	(-0.2037)	(1.6703)	(-0.5375)
$Net\ Income_{pre\text{-}Covid}$	-2.4666**	-0.1605	-0.2459	-0.3168	-10.7047
	(-2.0511)	(-0.3867)	(-0.8037)	(-0.3239)	(-1.3886)
$Deposits_{pre\text{-}Covid}$	-0.0448	-0.0201	-0.0498**	-0.0704	-0.9152
	(-0.9882)	(-1.2600)	(-2.0049)	(-0.9326)	(-1.4713)
$Market\ Funding_{pre\text{-}Covid}$	-0.0011	-0.0153**	0.0036	-0.0035	-0.0754
	(-0.0444)	(-2.0519)	(0.3843)	(-0.0901)	(-0.2031)
$LLP_{pre\text{-}Covid}$	0.7328	0.1216	0.4114*	0.1030	5.3291
	(1.4224)	(0.5309)	(1.8001)	(0.0884)	(0.6011)
$Tier\ I_{pre\text{-}Covid}$	-0.1169	-0.1130***	-0.0519*	-0.0722	-1.2876
	(-1.2079)	(-4.1220)	(-1.9466)	(-0.4497)	(-1.1201)
Intercept	Yes	Yes	Yes	Yes	Yes
Observations	92	92	92	92	92
Adj R-sq	0.410	0.740	0.728	0.575	0.697
Country FEs	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 3. This table shows the results of Equation (1) regression models. The dependent variables: *loan market share (MS Loans),* the ratio of the loans of a single bank in 2020 to the total loans of the sample for 2020; *deposit market share (MS Deposits),* the ratio of the deposits of a single bank in 2020 to the total loans of the sample in 2020; *ln(Operating revenue),* the logarithmic transformation of total operating revenue in € billion in 2019; *ROA,* the return on assets in 2020; *Tobin Q,* the logarithmic transformation of the book to market value in 2020. *Payment* is a dummy variable that takes value one if a bank has a payment institution and zero otherwise. The control variables are: *Size* is the value of total assets in € billion in 2019; *Loans* is the ratio of loans in € billion in 2019 to total assets in 2019; *Equity* is the ratio of equity in € billion in 2019 to total assets in 2019; *Net income* is the ratio of net income in € billion in 2019 to total assets for 2019; *Deposits* is the ratio of deposits in € billion for 2019 to total assets in 2019; *LLP* is the ratio of loan loss provisions in € billion in 2019 to total assets in 2019; *Tier 1* is the ratio of equity capital and disclosed reserves to total risk-weighted assets in 2019. *Market funding* is the ratio of short-term market debt in € billion in 2019 to total assets in 2019. All columns include country fixed effects. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)
Variables	*Loans MS*	*Deposits MS*	*ln(Operating Revenue)*	*ROA*	*Tobin Q*
Payment $_{pre\text{-}Covid}$	0.0001***	-0.0000	0.2127*	0.0002	-0.8416**
	(3.5848)	(-0.1189)	(1.7045)	(0.2652)	(-2.4058)
Size $_{pre\text{-}Covid}$	0.0000***	0.0000***	0.9241***	0.0004**	0.1685*
	(3.9224)	(6.0739)	(25.6132)	(2.4488)	(1.6863)
Loans $_{pre\text{-}Covid}$		-0.0000	-0.9066***	-0.0015	1.9818**
		(-0.5724)	(-3.1106)	(-1.1133)	(2.5027)
Equity $_{pre\text{-}Covid}$	0.0000	-0.0001	9.4862***	0.0491***	-1.6810
	(0.0072)	(-1.6454)	(5.6265)	(5.0196)	(-0.3003)
Net Income $_{pre\text{-}Covid}$	-0.0034*	0.0001		0.5373***	11.8001
	(-1.9704)	(0.4248)		(11.3471)	(0.4371)
Deposits $_{pre\text{-}Covid}$	-0.0003***		-0.8161	-0.0012	4.4119***
	(-3.7128)		(-1.5908)	(-0.4215)	(2.7105)
Market Funding $_{pre\text{-}Covid}$	-0.0000	0.0000**	-0.0036	0.0056***	0.0402
	(-0.2851)	(2.3550)	(-0.0108)	(3.5076)	(0.0429)
LLP $_{pre\text{-}Covid}$	0.0030**	-0.0000	18.5549**	-0.0501	21.1260
	(2.2147)	(-0.0826)	(2.3940)	(-1.3669)	(1.0173)
Tier I $_{pre\text{-}Covid}$	-0.0002	-0.0000	-0.9965	-0.0044	7.5081**
	(-1.2136)	(-0.2923)	(-0.8803)	(-0.8200)	(2.3340)
Intercept	Yes	Yes	Yes	Yes	Yes
Observations	88	88	89	88	84
Adj R-sq	0.739	0.958	0.974	0.955	0.830
Country FEs	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 4. This table shows the results of the Equation (2) regression models. The dependent variable is *SRISK*. This variable is calculated as the difference between the book value of debt and the long-run marginal expected shortfall. *Payment* is a dummy variable that takes value one if a bank has a PSRI and zero otherwise. Bank-specific variables: *Market Beta* is the beta of the market for the period of our sample; *Asset Beta* is the value of the market beta discount of leverage from 2019; *Liquid Asset* is the ratio of total liquid assets in 2019 to total bank assets in 2019; *Inter Bank* is total interbank liquidity in 2019; *Size* is the log of the value of total assets in €billion in 2019; *Loans* is the ratio of loans to total bank assets in € billion in 2019; *Equity* is the ratio of equity to bank total assets in € billion in 2019; *Net income* is the ratio of net income to bank total assets in € billion in 2019; *Deposits* is the ratio of deposits to bank total assets in € billion for 2019. *LLP* is the ratio of loan loss provisions to bank total assets in € billion in 2019. *Tier 1* is the ratio of regulatory capital to bank total risk-weighted assets in 2019. *Market funding* is the ratio of short-term market debt to bank total assets in € billion in 2019. All columns include country fixed effects. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.001.

Variables	(1) *SRISK Ratio (Jan-Jun 2020)*	(2) *SRISK Ratio (Jan-Jun 2020)*	(3) *SRISK Ratio (Jan-Jun 2020)*	(4) *SRISK Ratio (Jan-Jun 2020)*
*Payment*Market Beta*	-0.0043			
	(-0.3612)			
*Payment*Asset Beta*		0.0028		
		(0.8829)		
*Payment*Liquid Asset*			-0.0008***	
			(-7.5841)	
*Payment*InterBank*				-0.0001***
				(-7.5841)
$Size_{2019}$	0.0000	0.0000	-0.0000	0.0000
	(0.3456)	(0.4538)	(-1.6091)	(1.0651)
$Loans_{2019}$	0.0000	0.0002	0.0012***	-0.0002
	(0.0209)	(0.2553)	(3.6727)	(-0.6953)
Equity 2019	-0.0060*	-0.0081**	-0.0019	-0.0009
	(-1.6932)	(-2.1087)	(-1.4001)	(-0.6809)
Net Income 2019	-0.0147	-0.0215	-0.0059	-0.0047
	(-0.8633)	(-1.1855)	(-0.9089)	(-0.7756)
Deposits 2019	-0.0001	-0.0005	-0.0018***	0.0004
	(-0.1254)	(-0.4089)	(-3.7289)	(0.8808)
Market Funding 2019	-0.0004	-0.0005	-0.0017***	0.0003
	(-0.6976)	(-0.7420)	(-5.0891)	(0.9072)
LLP 2019	-0.0009	-0.0041	-0.0030	-0.0072
	(-0.0584)	(-0.2517)	(-0.5101)	(-1.3128)
Tier I 2019	0.0019	0.0024	0.0005	0.0004
	(0.8594)	(1.0367)	(0.6493)	(0.4438)
Intercept	Yes	Yes	Yes	Yes
Observations	91	92	91	88
Adj R-sq	0.964	0.881	0.984	0.987
Country FEs	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 5. This table shows the results of the Equation (2) regression models. The dependent variables is *SRISK*, which is the measure of systemic risk provided by V-Lab (Stern NYU) calculated as the difference between the book value of debt and the long-run marginal expected shortfall. *Payment* is a dummy variable that takes value one if a bank has a PSRI and zero otherwise. Control variables: *Size* is the value of total assets in € billion in 2019; *Loans* is the ratio of loans in € billion in 2019 to total assets in 2019; *Equity* is the ratio of equity in € billion in 2019 to total assets in 2019; *Net income* is the ratio of net income in € billion in 2019 to total assets in 2019; *Deposits* is the ratio of deposits in € billion in 2019 to total assets in 2019; *LLP* is the ratio of loan loss provisions in € billion in 2019 to total assets in 2019; *Tier 1* is the ratio of equity capital and disclosed reserves to total risk-weighted assets in 2019. *Market funding* is the ratio of short-term market debt in € billion in 2019 to total assets in 2019. All columns include country fixed effects. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.001.

Variables	(1) *SRISK Ratio*	(2) *SRISK Ratio*	(3) *SRISK Ratio*	(4) *SRISK Ratio*	(5) *SRISK Ratio*	(6) *SRISK Ratio*	(7) *SRISK Ratio*	(8) *SRISK Ratio*
*Payment*Size*	0.0041***							
	(32.5754)							
*Payment*Loans*		0.0034**						
		(2.6406)						
*Payment*Equity*			-0.0347***					
			(-5.0858)					
*Payment*Net Income*				-0.1454***				
				(-9.0915)				
*Payment*Deposits*					0.0068			
					(1.5485)			
*Payment*Market Funding*						-0.0234***		
						(-9.7278)		
*Payment*LLP*							-0.0433	
							(-1.3500)	
*Payment*Tier I*								0.0001
								(0.0109)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92	92	90	92	92	92	91	91
Adj R-sq	0.988	0.856	0.926	0.968	0.827	0.973	0.894	0.841
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 6. This table shows the results of the Equation (1) regression models that include the interaction terms based on the supply chain network measure presented in Equation (3). *Srisk* is the measure of systemic risk provided by V-Lab (Stern NYU) calculated as the difference between the book value of debt and the long-run marginal expected shortfall. SNC measures are based on calculations of eq. (3). *Payment* is a dummy variable that takes value one if a bank has a PSRI and zero otherwise. Control variables: *Size* is the value of total assets in € billion in 2019; *Loans* is the ratio of loans in € billion in 2019 to total assets in 2019; *Equity* is the ratio of equity in € billion in 2019 to total assets in 2019; *Net income* is the ratio of net income in € billion in 2019 to total assets in 2019; *Deposits* is the ratio of deposits in € billion in 2019 to total assets in 2019; *LLP* is the ratio of loan loss provisions in € billion in 2019 to total assets in 2019; *Tier 1* is the ratio of equity capital and disclosed reserves to total risk-weighted assets in 2019. *Market funding* is the ratio of short-term market debt in € billion in 2019 to total assets in 2019. All columns include country fixed effects. Robust t-statistics in parentheses. *** p<0.10, ** p<0.05, * p<0.01.

Variables	(1) *BHR*	(2) *Volatility*	(3) *SRISK Ratio*	(4) *Beta*	(5) *Asset Beta*	(6) *BHR*	(7) *Volatility*	(8) *SRISK Ratio*	(9) *Market Beta*	(10) *Asset Beta*
*Payment*SNC_Internal*	0.0040	0.0018	0.0009***	0.0154	0.0420					
	(0.9244)	(0.9216)	(3.3835)	(1.1310)	(0.5562)					
*Payment*SNC_External*						0.0038	0.0020	0.0005	-0.0246*	-0.1178
						(1.0850)	(1.1779)	(1.2041)	(-2.0039)	(-1.1549)
Size2019	0.0016	-0.0004	0.0000	0.0076	-0.0215	0.0033*	0.0008	0.0000	0.0011	0.0151
	(1.0703)	(-0.6259)	(0.2441)	(1.5579)	(-0.7950)	(1.9095)	(0.8734)	(0.1749)	(0.1788)	(0.2973)
Loans 2019	-0.0191	0.0006	0.0007	0.0495	0.5696**	0.0051	-0.0061	0.0005	-0.0099	0.2413
	(-1.5713)	(0.1038)	(0.9469)	(1.2828)	(2.6582)	(0.4206)	(-1.0192)	(0.3211)	(-0.2354)	(0.6896)
Equity 2019	0.1623**	0.0114	-0.0084*	0.1246	-1.3071	0.1168	0.0151	-0.0158	-0.0948	-5.0987**
	(2.1926)	(0.3315)	(-1.7688)	(0.5294)	(-1.0000)	(1.5109)	(0.3948)	(-1.5768)	(-0.3495)	(-2.2673)
Net Income 2019	-1.5940***	-0.1586	-0.0284	-0.5627	1.9802	-1.0424***	-0.0953	-0.0198	-1.0308	-9.3798
	(-4.5762)	(-0.9821)	(-1.2770)	(-0.5079)	(0.3219)	(-3.0314)	(-0.5597)	(-0.4434)	(-0.8545)	(-0.9376)
Deposits2019	-0.0188	-0.0253**	-0.0016	-0.1149	-0.3618	-0.0586**	-0.0217	-0.0004	0.1151	0.0296
	(-0.7656)	(-2.2254)	(-1.0352)	(-1.4719)	(-0.8348)	(-2.1066)	(-1.5763)	(-0.1036)	(1.1791)	(0.0365)
Market Funding 2019	0.0061	-0.0142**	-0.0009	-0.0314	0.0298	-0.0091	-0.0059	-0.0003	0.0207	-0.0641
	(0.4956)	(-2.4795)	(-1.1784)	(-0.8017)	(0.1368)	(-0.6998)	(-0.9161)	(-0.1765)	(0.4522)	(-0.1692)
LLP2019	0.7637**	0.3126**	0.0040	-0.5176	-3.9730	0.7697**	0.2280	0.0369	-0.5918	1.8755
	(2.4735)	(2.1841)	(0.2041)	(-0.5271)	(-0.7286)	(2.5831)	(1.5454)	(0.9539)	(-0.5662)	(0.2163)
Tier I 2019	-0.0820*	-0.0841***	0.0016	-0.1221	-0.6798	-0.0660	-0.1004***	-0.0050	-0.4225***	-3.1353**
	(-1.8626)	(-4.1250)	(0.5769)	(-0.8724)	(-0.8745)	(-1.4672)	(-4.5091)	(-0.8633)	(-2.6782)	(-2.3965)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88	88	88	88	88	80	80	80	80	80
Adj R-sq	0.613	0.843	0.847	0.635	0.866	0.733	0.903	0.855	0.685	0.779
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7. This table shows the results of the eq (2) regression model model. The main variable is Srisk, which is the measure of systemic risk provided by V-Lab (Stern NYU) calculated as the difference between the book value of debt and the long-run marginal expected shortfall. The SNC measures are based on calculations of eq. (3). Payment is a dummy variable that takes value one if a bank has a payment institution and zero otherwise. Control variables: *Size* is the value of total assets in € billion in 2019; *Loans* is the ratio of loans in € billion in 2019 to total assets in 2019; *Equity* is the ratio of equity in € billion in 2019 to total assets in 2019; *Net income* is the ratio of net income in € billion in 2019 to total assets in 2019; *Deposits* is the ratio of deposits in € billion in 2019 to total assets in 2019; *LLP* is the ratio of loan loss provisions in € billion in 2019 to total assets in 2019; *Tier 1* is the ratio of equity capital and disclosed reserves to total risk-weighted assets in 2019. *Market funding* is the ratio of short-term market debt in € billion in 2019 to total assets in 2019. All columns include country fixed effects. Robust t-statistics in parentheses. *** p<0.10, ** p<0.05, * p<0.01.

Variables	(1) *SRISK Ratio*	(2) *SRISK Ratio*	(3) *SRISK Ratio*	(4) *SRISK Ratio*
*Payment*SNC_Internal_S&C*	0.0221***			
	(79.3763)			
*Payment*SNC_Internal_Partnership*		-0.0001		
		(-0.3480)		
*Payment*SNC_External_S&C*			0.0008	
			(0.7307)	
*Payment*SNC_External_Partnership*				0.0134***
				(19.5170)
Size2019	0.0002**	0.0002*	0.0016***	0.0002
	(2.4443)	(1.8693)	(5.0946)	(1.2846)
Loans 2019	-0.0011	0.0003	-0.0096***	0.0012
	(-1.6539)	(0.2576)	(-3.2406)	(0.9619)
Equity 2019	-0.0049	-0.0019	0.0267	-0.0097
	(-1.2024)	(-0.3184)	(1.3989)	(-1.2583)
Net Income 2019	-0.0197	-0.0372	-0.2245**	-0.0404
	(-0.9994)	(-1.2729)	(-2.5492)	(-1.1477)
Deposits2019	-0.0002	-0.0004	0.0069	-0.0036
	(-0.1871)	(-0.2125)	(0.9909)	(-1.3989)
Market Funding 2019	-0.0021***	-0.0002	0.0028	-0.0009
	(-3.0539)	(-0.1805)	(0.8407)	(-0.6804)
LLP2019	0.0006	-0.0059	0.2624***	0.0210
	(0.0338)	(-0.2323)	(3.4853)	(0.7205)
Tier I 2019	0.0020	0.0025	-0.0355***	-0.0010
	(0.8130)	(0.6792)	(-3.0103)	(-0.2148)
Intercept	Yes	Yes	Yes	Yes
Observations	88	87	80	81
Adj R-sq	0.995	0.580	0.809	0.984
Country FEs	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix 1. Variables included in the paper with descriptions and data sources.

Market Characteristics	Description	Source
BHR	Buy-and-hold bank stocks returns	Thomson Reuters Eikon
Volatility	Stock return volatility	Thomson Reuters Eikon
SRISK Ratio	The difference between the book value of debt and the long-run marginal expected shortfall	V-Stern Lab
Market Beta	Beta of the market for the period of our sample	Thomson Reuters Eikon
Asset Beta	The market beta discount for leverage	Thomson Reuters Eikon
Bank Characteristics		
Payments	Dummy variable that takes value one if a bank has a PSRI and zero otherwise	Hand collected from ECB
Size	Total assets	BankFocus
Loans	The ratio of loans to total assets	BankFocus
Deposit	The ratio of total deposits to bank total assets.	BankFocus
Equity	The ratio of equity to total assets	BankFocus
LLP	The ratio of total loan loss provisions to bank total assets.	BankFocus
Tier 1	The ratio of Tier 1 capital to risk-weighted assets.	BankFocus
InterBank	Total interbank liquidity	BankFoucs
Market funding	The ratio of the short-term market debt to total assets	BankFocus
Loans MS	The ratio of the loans of a single bank to the total loans in the sample	Own estimations based on data from BankFocus
Deposits MS	The ratio of the deposits of a single bank to the total loans of the sample	Own estimations based on data from BankFocus
ln(Operating Revenue)	The logarithmic transformation of total operating revenue	Own estimations based on data from BankFocus
ROA	Return on assets	BankFocus
Tobin Q	The logarithmic transformation of the book to market value	Own estimations based on data from BankFocus
Liquid Asset	The ratio of total liquid assets to total bank assets	Own estimations based on data from BankFocus
Supply chain network		
SNC_Internal	Total number of internal supply chain relationships based on eq. (3)	Own estimations based on data from FactSet
SNC_External	Total number of external supply chain relationships based on eq. (3)	Own estimations based on data from FactSet
SNC_Internal_S&C	Total number of internal supply chain relationships with suppliers, customers and competitors based on eq. (3)	Own estimations based on data from FactSet
SNC_Exteranl_S&C	Total number of external supply chain relationships with suppliers, customers and competitors based on eq. (3)	Own estimations based on data from FactSet
SNC_Internal_Partnership	Total number of internal supply chain relationships in partnerships based on eq. (3)	Own estimations based on data from FactSet
SNC_External_Partnership	Total number of external supply chain relationships in partnerships based on eq. (3)	Own estimations based on data from FactSet

Report of the activity

- **Policy papers**

Cambridge Centre for Alternative Finance. (2022). Global Covid-19 FinTech Market Impact and Industry Resilience Study. (Joint work with World Bank and World Economic Forum).

Cambridge Centre for Alternative Finance. (2022). Open Banking Implementation in Thailand, policy recommendations. (Joint work with Bank of Thailand).

- **Courses outside the PhD program**

Summer School in Empirical Tools/Applications in Banking and Macro-Finance, Graduate School of Economics, 2021

Executive course in Panel Data for Banking Sector Analysis, EUI Florence School Banking and Finance, 2021

Executive course in Fintech Innovation, Finance and Regulation, EUI Florence School Banking and Finance, 2020

- **Conferences**

International Finance and Banking Society (IFBAS), 2023 at Oxford University

Conference in Banking and Corporate Finance (EFiC), 2023

Day-Ahead PhD Workshop on Financial Intermediation, 2023 at Bayes Business School

European Finance Association, Doctoral workshop – Fintech, Blockchains & Cryptocurrency, 2022, at IESE

New (and Old) Challenges to Financial Intermediation, CEPR, 2023 at Bayes Business School

- **Teaching**

University of Bologna

Instructor for the MBA course in Finance & Fintech, Bologna Business School, 2021-22, 2022-23 and 2023-24

Teaching Assistant for the MSc course in Financial Markets and Products at the University of Bologna, 2021-22, 2022-23 and 2023-24

Teaching Assistant for the BA course in Banking at the University of Bologna, 2021-22, 2022-23, 2023-24

Instructor for the BA course in Investment at the University of Bologna, 2020-21 and 2021-22

Teaching Assistant for the BA course in Strategy, Organization, and Market at the University of Bologna, 2019-20

European University Institute - Florence School Banking and Finance

Academic referent and instructor for EU-SDFA foundational course, EUI, 2022-23 and 2023-24

Instructor for Central Banking and Banking Supervision, 2023-24, Executive Education Programme for ECB & SSM

Academic referent for SupTech advance course for EU-SDFA, 2022-23 and 2023-24

Academic referent for SupTech hackathon advance course for EU-SDFA, 2023-24

Academic referent and instructor for Data-driven Business Models & Data Sharing in Finance advance course for EU-SDFA, 2023-24

Academic referent for AI & ML in the financial sector online advance course for EU-SDFA, 2023-24

Academic referent for research & policy workshop for EU-SDFA, 2023-24