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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.

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

1 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).

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.2 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 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.

2 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.

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).[3] 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.[4] 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 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.

3 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).

4 https://www.berlin-group.org/psd2-access-to-bank-accounts

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).[5] 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.[6]

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.

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

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		

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 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 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 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.

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. $P_{f,\,b}$ 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, $P_{b,t}$ is a bank*quarter fixed effect and $Y_{f,t}$ 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:

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

This is equation 1 with interaction terms introduced. In the staggered decomposition analysis is the product of the post-treatment period and the group dummy, , 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

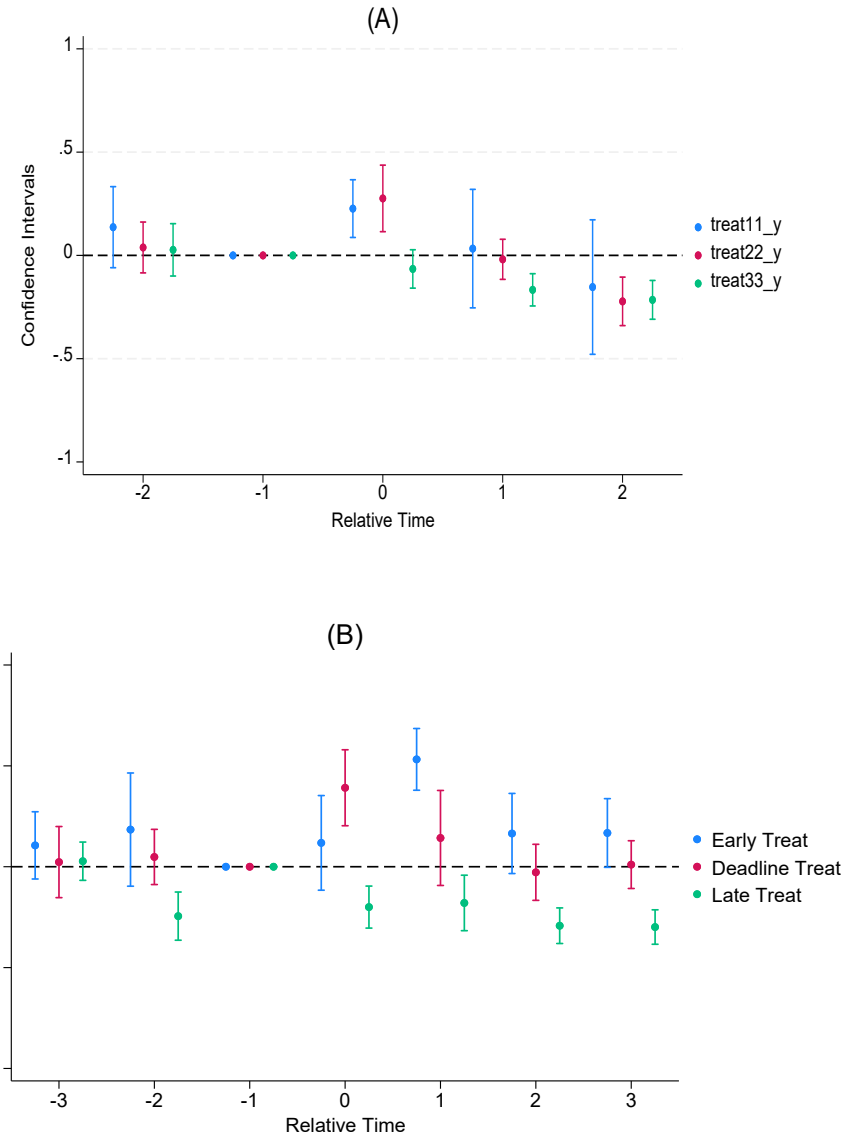
This section presents the results of the previously described empirical analysis following the methodological steps to identify the impact of open banking frameworks on TradFis lending. Before presenting the main empirical results, it first focuses on a graphic analysis related to the parallel trends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

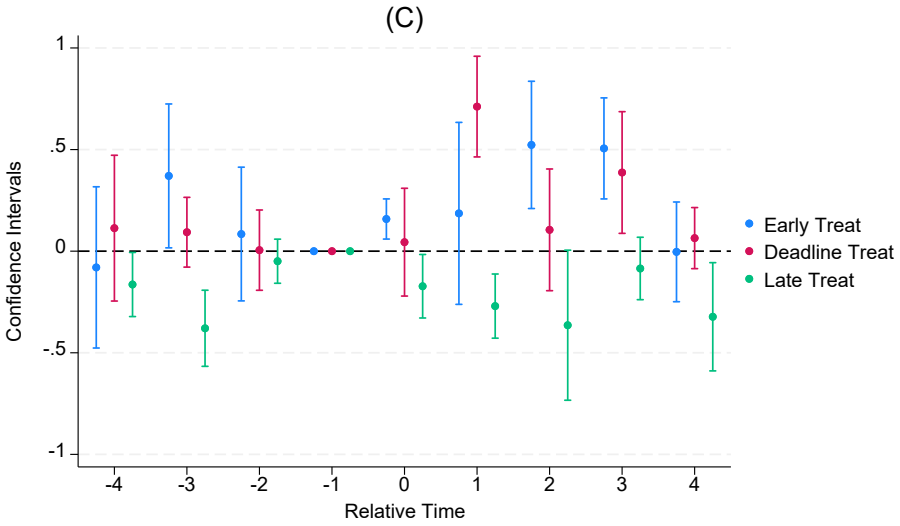
Figure 1 displays the coefficient plot for equation 1 of the fixed effects with time frames for the different cohorts, which allows us to examine the heterogeneity effect of open banking frameworks across the EU. Zero represents the introduction of the PSD2. Panel A shows the dynamics of the year fixed 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.

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.





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.

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.

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.

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.

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.

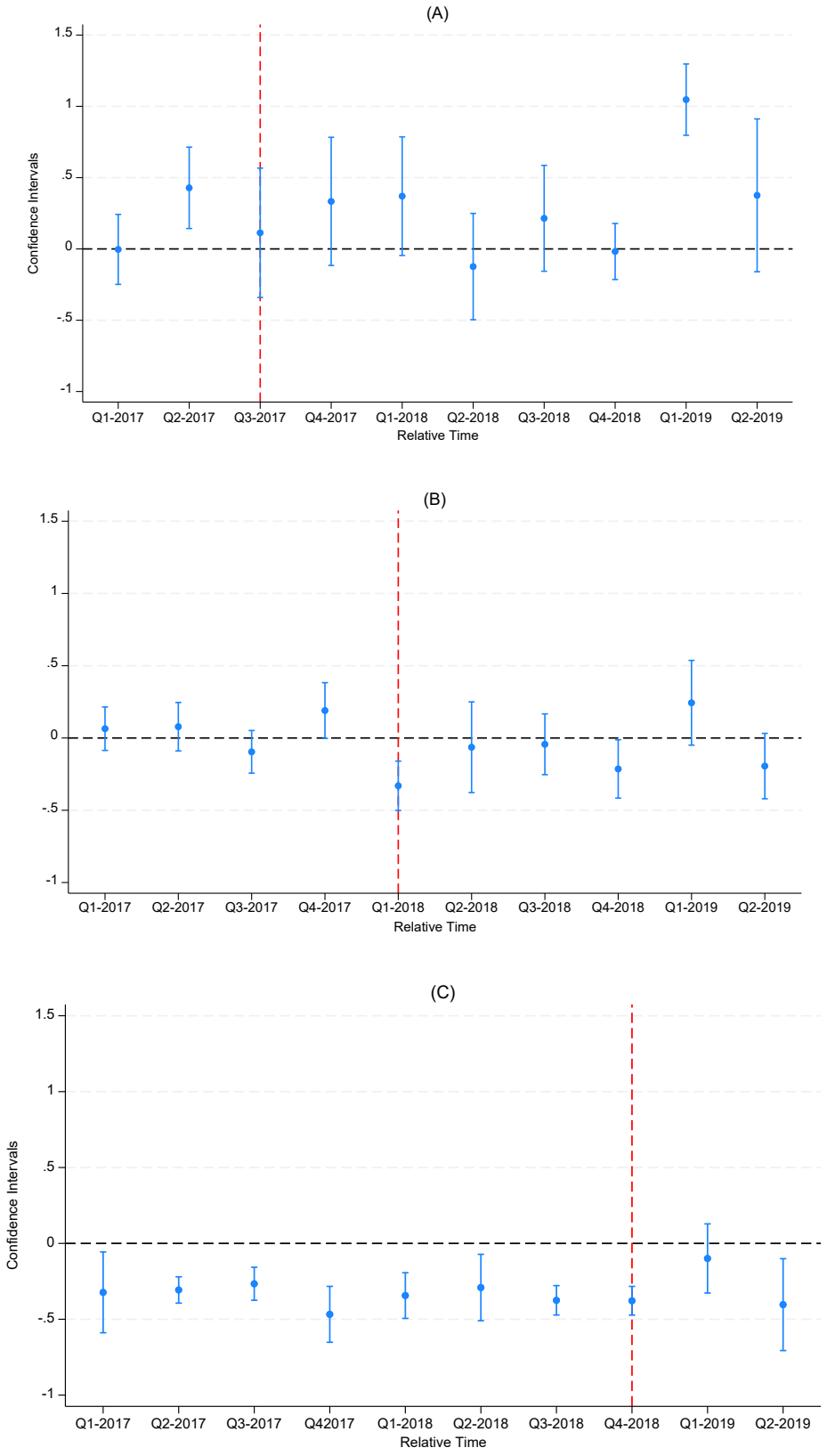


Table 5.

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 overLIBOR 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 * Treatment							0.0375	0.0449	0.0500	0.0083	0.0111	0.0150
							(1.0738)	(1.1138)	(0.7507)	(0.9519)	(0.4200)	(0.3927)
Deadline T.*Date Adoption* Treatment							0.1352***	0.1354***	0.1493**	0.0168*	-0.0011	0.0313
							(4.4224)	(3.0668)	(2.1567)	(1.8233)	(-0.0376)	(0.7899)
Late T.*Date Adoption * Treatment							0.0379***	0.0335*	0.0323	0.0112*	0.0053	0.0107
							(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

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.

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).

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%.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Ln(Spread)	Ln(Spread)	Ln(Spread)	Collateral	Collateral	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

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.

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

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).

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.

	(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
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

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.

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

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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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

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