Navigating the Digital Frontier: Unraveling the Impact of Bank Technology Innovations on Idiosyncratic and Systemic Risks

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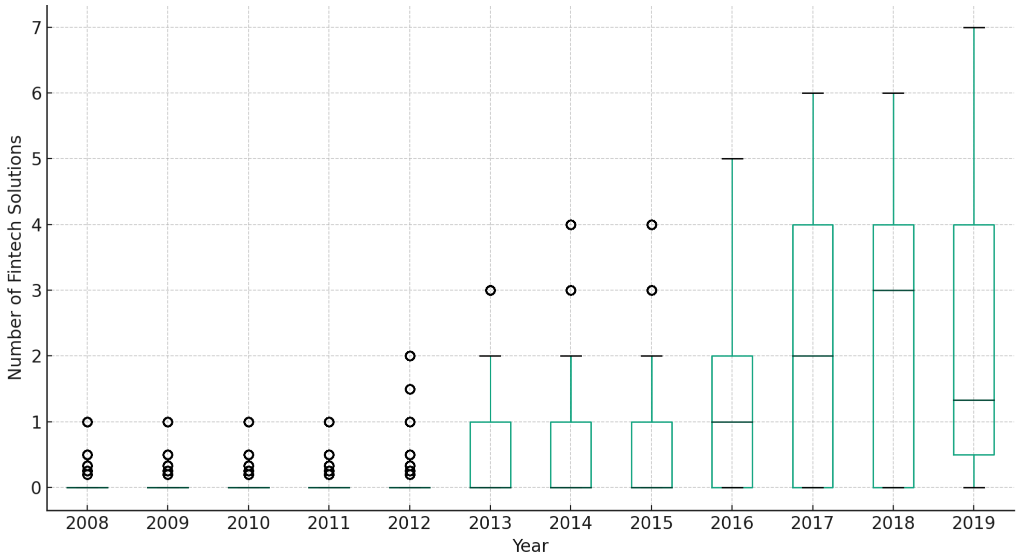
Research questions

What is the nature, scale and source of technological development at banks?

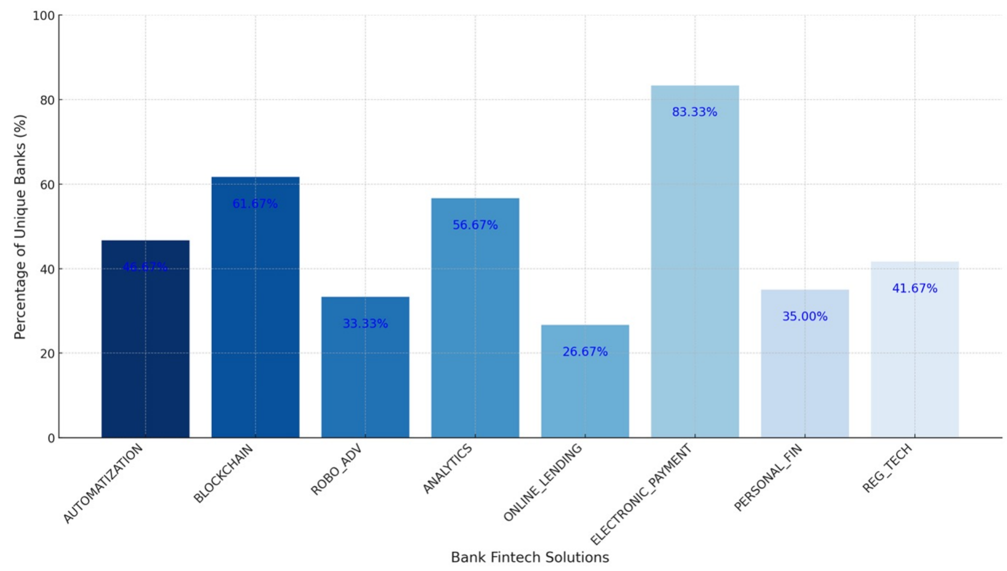
What is the impact of bank technological development on different sources of risks in the banking sector.

The banking sector is the largest beneficent of technological development , though differences between the banks and countries are significant.

Bank technological development over the years



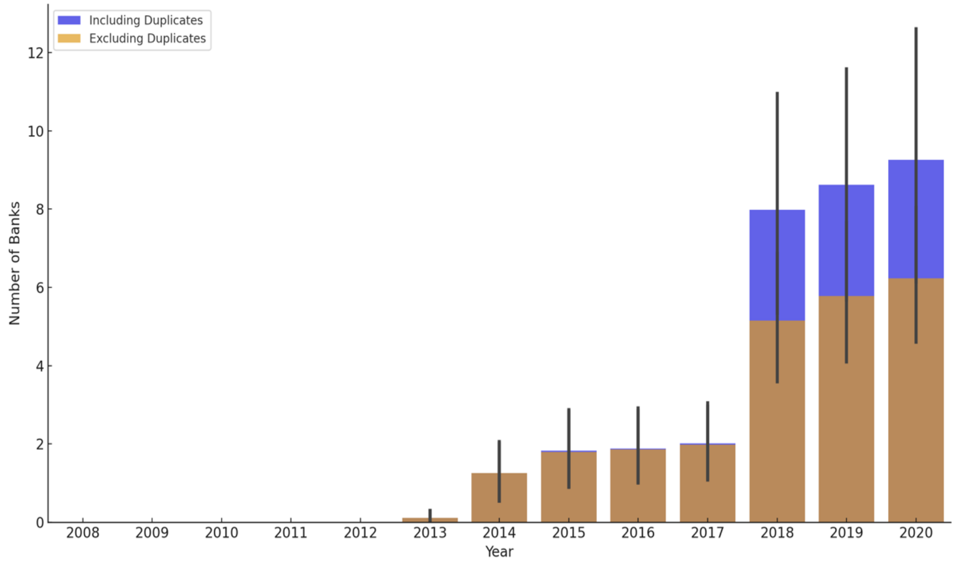
Percentage usage of bank fintech solutions



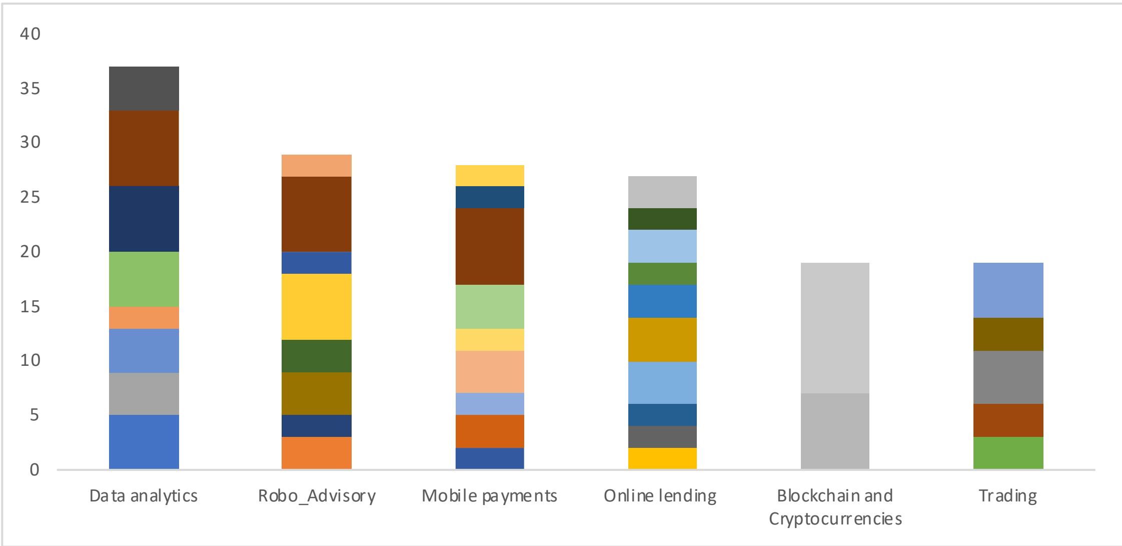
Souce: own elaboration

Concentration of technology providers in the banking sector

Scale of banks using the same technology providers over time



Scale of banks using the same technology providers over time



Source: Own elaboration

Sample

- We analyze the technological adoption by **63 largest European and US banks** over **the period of 2008 and 2019** which we then extend to 363 banks. We expand the sample to 393 other banks.
- We use **the data mining techniques** to identify the typology of technological solutions adopted by each bank over the sample period.
- To measure banks’ digitalization we use the **typology of technology adoption**: (AUT.SOFT), blockchain technology (BLOCKCHAIN), data analytics (ANALYTICS), lending solutions (LENDING), payments (PAYMENTS), personal finance (PERSON.FIN), and regulatory technology (REGULAT).
- **In the robustness,** we also use the **ratio of intangible asset to bank’s total asset** as an alternative measure for bank technological development.
- We also create an **innovation dummy**, the sum of all solutions a bank adopts in a given year.
- We also control for the **source of bank’s technology adoption**: investment, outsourcing and partnership with Fintech and **concentration of the technology providers** within the banking sector.

Source: Own elaboration

Methodology (part I)

- To identify the role of technology on banks' NPLs share we use the **Difference-in-Difference** (DID) approach where the treatment starts in 2011 (the first year after the financial crisis). Moreover, the **banks enter the treatment group if the number of solutions has increased the mean number of all solutions for the entire sample**, i.e., when it is higher than 4 **(high versus zero).**
- We compare the treatment banks (*HighAdopters*) to banks with lower numer of technological solutions (*LowAdopters*) or no adopted solutions (**control group**).
- The presence of systematic differences between the treatment and control groups in the sample is not an issue because the DID methodology does not rely on random assignment to treatment (Angrist and Pischke, 2009; Cameron and Trivedi, 2005). Indeed, **the identifying assumption is that the two groups follow the same trend in absence of treatment**. This is likely to happen in our setting because: **(i)** we include country and year-fixed effects, which are not included in a standard DID approach, **(ii)** the treatment and control groups are not fixed over time, i.e., at a given point an untreated bank enters in the treatment group when it is subject to a sharp increase in the digitalization; **(iii)** all banks experienced the same shock between 2008 and 2010.

Methodology (part II): Measures of risk

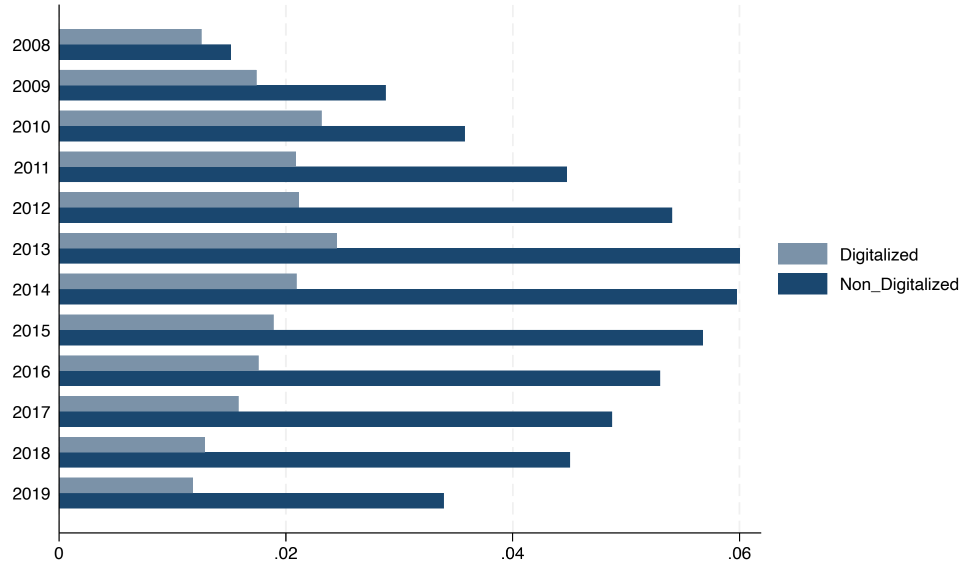
Credit Risk

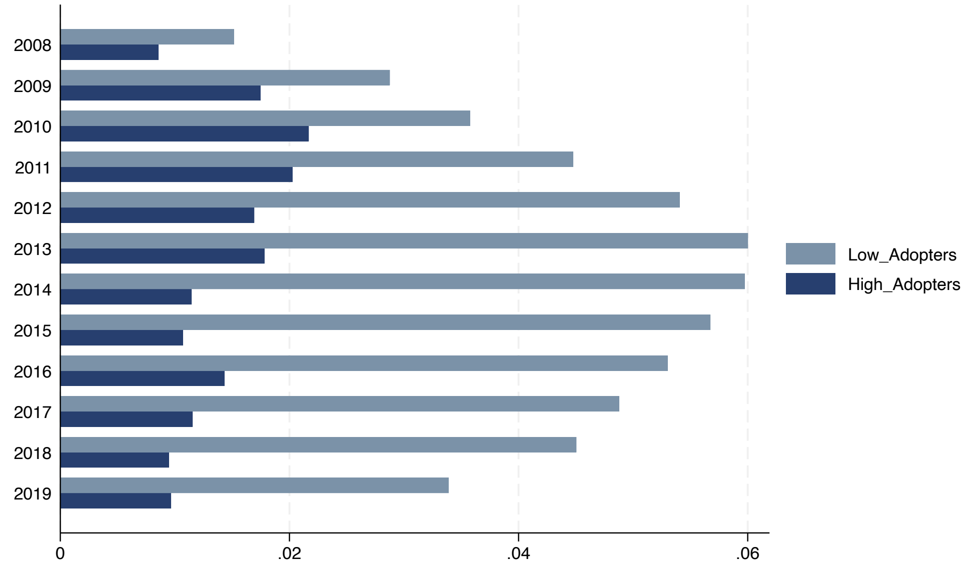
- Non-performing loans to bank's total loans

Systemic Risk

- SRISK (%): The proportional contribution of each bank's SRISK to the total positive SRISK of the financial system.
- Absolute SRISK: Expressed in mln USD; the expected fractional loss of equity when the MSCI All-Country World Index falls by the crisis threshold (40%) within a six-month period.

Average distribution of banks' NPLs between different groups





Static DID regression: NPLs ratio

VARIABLES	(1) NPL_Ratio	(2) NPL_Ratio	(3) NPL_Ratio	(4) NPL_Ratio
High_Adopters	0.00532	0.00873	0.00359	0.0122
	(0.00506)	(0.00540)	(0.00577)	(0.00765)
Treatment_Years	0.0200**	0.0163*	0.00408	-0.00428
	(0.00847)	(0.00924)	(0.0107)	(0.0135)
High_Adopters*Treatment_Years	-0.0197**	-0.0180*	-0.0189**	-0.0193**
	(0.00861)	(0.00906)	(0.00754)	(0.00726)
Observations	639	639	528	445
R-squared	0.058	0.098	0.202	0.229
Bank Controls				YES
Macro Controls			YES	YES
Bank FE		YES	YES	YES
Time FE	YES	YES	YES	YES

Dynamic DID regression: NPLs ratio

	(1) NPL_share	(2) NPL_share	(3) NPL_share	(4) NPL_share
YearDummy2009*treated banks	-0.00557**	-0.00560**	0.000180	-0.00943
	(0.00225)	(0.00225)	(0.0104)	(0.00932)
YearDummy2010 *treated banks	-0.0080	-0.0082	-0.0026	-0.0073
	(0.0053)	(0.0052)	(0.0108)	(0.0051)
YearDummy2011 *treated banks	-0.0187**	-0.0187**	-0.0236**	-0.0236**
	(0.00737)	(0.00740)	(0.00935)	(0.00960)
YearDummy2012*treated banks	-0.0292***	-0.0291***	-0.0370***	-0.0338***
	(0.0100)	(0.0100)	(0.0104)	(0.0113)
YearDummy2013*treated banks	-0.0348***	-0.0348***	-0.0335***	-0.0234*
	(0.0129)	(0.0129)	(0.0110)	(0.0138)
…				
YearDummy2019*treated banks	-0.0143	-0.0141	-0.0574**	-0.0640**
	(0.0110)	(0.0111)	(0.0281)	(0.0299)
Observations	537	537	436	417
R-squared		0.112	0.253	0.378
Number of banks	55	55	55	55
Bank FE	YES	YES	YES	YES
Time FE		YES	YES	YES
Time Varying Macroeconomic Controls		YES	YES	YES
Time Varying Bank Controls		YES	YES	YES

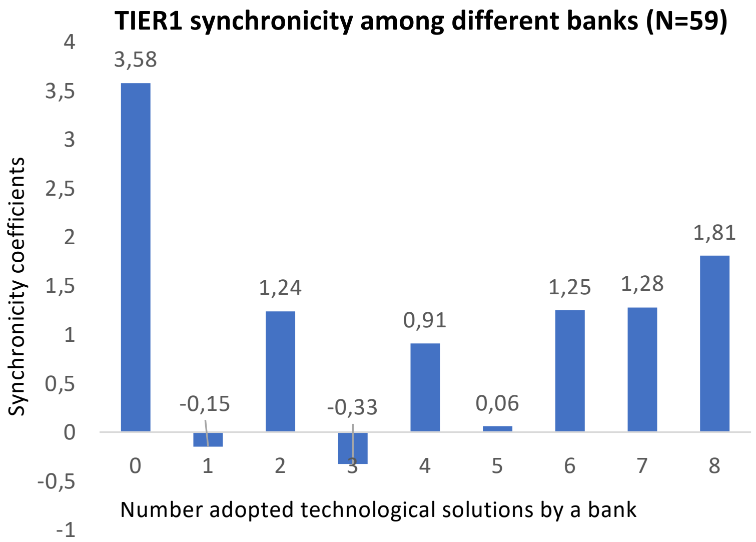
Staggered DID regression: NPLs ratio

	(1) NPL_Ratio	(2) NPL_Ratio	(3) NPL_Ratio	(4) NPL_Ratio
High_Adopters*Treatment_Years	-0.0239**	-0.0223**	-0.0232**	-0.0199***
	(0.0107)	(0.0110)	(0.00907)	(0.00615)
Observations	537	537	436	417
R-squared	0.067	0.108	0.221	0.374
Bank controls				YES
Macro controls			YES	YES
Bank FE		YES	YES	YES
Time FE	YES	YES	YES	YES

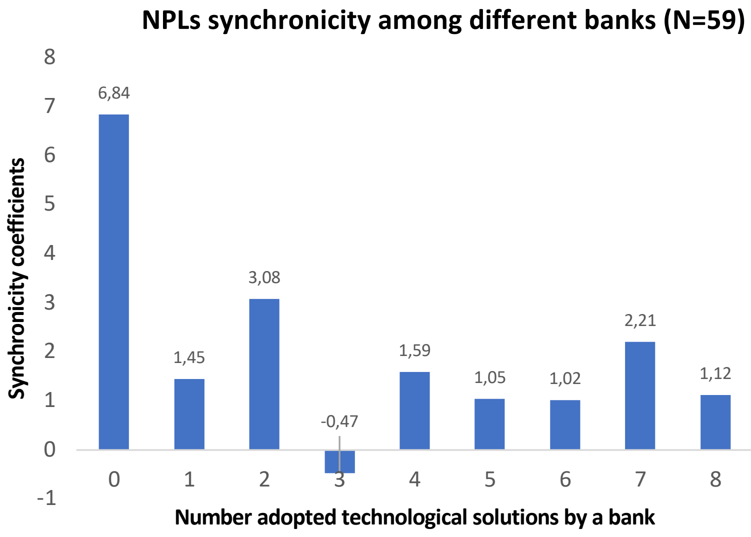
Systemic Risk Examination - Synchronicity Analysis

- To analyze the systemic risk between banks we start with the **synchronicity regressions** to analyze the correlation between different risk indicators **(NPLs share, TIER1 capital level)** in the banking sector as well as a correlation between the algorithmic decisions **embedded in the technological solutions** adopted by banks. The idea of the synchronicity analysis can be found by Chan et al. (2013).
- To analyze the **impact of digitalization on the systemic banking sector** we use the dynamic fixed-effect estimator **(both bank-and time fixed effects),** adding also other bank and country control variables as one-period lags to avoid the simultaneous bias.
- We **use the SRISK** measures in **absolute terms SRISK** and **relative terms (%SRISK)** to measure the systemic risk. The measure shows banks' capital shortage when the stock market index drops by 40% in a six-month period. The index (Acharya et al., 2012; Acharya et al., 2017; Brownlees and Engle, 2017; Engle et al., 2012).

Synchronicity regressions



Lower co-movement of TIER1 among the technologically advanced banks, as compared to no solution banks.



Lower co-movement of NPLs among the technologically advanced banks, as compared to no solution banks.

Impact of technological solutions on systemic risk measures

	SRISK%	SRISK
TECH_DEV	**-0.185****	**-3.0e+03*****
	(0.074)	**(687.146)**
L1.SIZE	0.725**	2.5e+04***
	(0.330)	(3063.665)
L1. EQUITY RATIO	-0.136**	-1.5e+03**
	(0.064)	(593.073)
L1.LOAN ACTIVITY	-0.013	66.270
	(0.012)	(111.293)
L1.NON_INTEREST	-0.005	-53.520
	(0.007)	(62.074)
L1.DEPOSIT RATIO	0.004	17.070
	(0.006)	(53.517)
L1.NPL_SHARE	0.008	639.514***
	(0.025)	(229.486)
L1. ROA	-0.140	-492.933
	(0.165)	(1531.313)
GDP	0.008	597.517
	(0.045)	(414.323)
INFLATION	-0.046	-1.3e+03
	(0.087)	(807.036)
Observations	491	491
R-squared	0.874	0.900
Bank FE	Yes	Yes
Time FE	Yes	Yes

Impact of technological solutions on systemic risk measures

	(1) SRISK	(2) SRISK	(3) SRISK	(4) SRISK	(5) SRISK	(6) SRISK	(7) SRISK	(8) SRISK
TECH_DEV	0.559*	0.539*	0.707**	0.612*	0.534	0.786**	0.550*	0.517
AUT.SOFT	0.097							
	(0.286)							
BLOCKCHAIN		**-0.613*****						
		(0.208)						
ROBO-ADV.			**-0.669****					
			(0.263)					
ANALYTICS				-0.507**				
				(0.224)				
LENDING					0.231			
					(0.329)			
PAYMENTS						**-0.744*****		
						(0.251)		
PERSON.FIN							0.143	
							(0.333)	
REGULAT.								0.457*
								(0.255)
Observations	491	491	491	491	491	491	491	491
R-squared	0.872	0.875	0.874	0.874	0.873	0.875	0.872	0.873
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Impact of technology providers' concentration on systemic risk

	SRISK%	SRISK%	SRISK	SRISK
Tech_Dev	-0.111	-0.108**	-2.2e+03***	-392.676
	(0.075)	(0.054)	(698.178)	(505.509)
Sharing	**0.002**		**46.121*****	
	(0.002)		**(17.539)**	
Observations	491	491	491	491
R-squared	0.891	0.892	0.912	0.911
Bank controls	YES	YES	YES	YES
Macro controls	YES	YES	YES	YES
BANK FE	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES

Robustness:

Using Intangible asset ratio at the 75 quantile variable distribution as an alternative for HighAdopters

	(1) NPL_Ratio	(2) NPL_Ratio	(3) NPL_Ratio	(4) NPL_Ratio
YearDummy2009*treated banks	-0.00169	-0.00196	0.000843	-0.00363
	(0.00340)	(0.00345)	(0.00376)	(0.00641)
YearDummy2010*treated banks	-0.00718	-0.00712	-0.00415	-0.00732
	(0.00507)	(0.00512)	(0.00535)	(0.00618)
YearDummy2011*treated banks	**-0.0201*** **	**-0.0203** **	**-0.0176** **	**-0.0152** **
	(0.00774)	**(0.00780)**	**(0.00830)**	**(0.00669)**
YearDummy2012*treated banks	-0.0297***	-0.0302***	-0.0287***	-0.0307***
	(0.00911)	(0.00916)	(0.00882)	(0.0111)
YearDummy2013*treated banks	-0.0324***	-0.0327**	-0.0302**	-0.0172**
	(0.0125)	(0.0125)	(0.0125)	(0.00754)
YearDummy2014*treated banks	-0.0288***	-0.0293***	-0.0268**	-0.0161**
	(0.0105)	(0.0106)	(0.0101)	(0.00716)
YearDummy2015*treated banks	-0.0253**	-0.0258**	-0.0238**	-0.0134*
	(0.0107)	(0.0108)	(0.0102)	(0.00680)
YearDummy2016*treated banks	-0.0251**	-0.0256**	-0.0257**	-0.0186**
	(0.0109)	(0.0109)	(0.0111)	(0.00825)
YearDummy2017*treated banks	-0.0194***	-0.0204***	-0.0171***	-0.0161**
	(0.00621)	(0.00657)	(0.00638)	(0.00708)
YearDummy2019*treated banks	**-0.0205*** **	**-0.0214*** **	**-0.0363*** **	**-0.0457*** **
	(0.00735)	**(0.00769)**	**(0.0117)**	**(0.0139)**
Observations	604	604	501	476
R-squared	0.04	0.167	0.213	0.464
Number of banks	58	58	57	57
Time FE	YES	YES	YES	YES
Bank FE		YES	YES	YES
Time-Varying Macroeconomic Controls		YES	YES	YES
Time-Varying Bank Controls		YES	YES	YES

Robustness:

Using Intangible asset ratio as an alternative for number of technological solutions

	(1) SRISK%	(2) SRISK	(3) IRMES	(4) BETA	(5) CORR.	(6) VOL.	(7) LEV.
INTANGIBLE_ASSET	**-0.073*** **	**-478.648*** **	**-0.612*** **	**-0.021*** **	**0.002**	**-0.649** **	**-0.084**
	(0.023)	**(176.932)**	**(0.213)**	**(0.007)**	**(0.002)**	**(0.372)**	**(0.235)**
L1.SIZE	-0.003	34.881	0.771*	0.021	0.019***	-1.768**	0.308
	(0.049)	(372.941)	(0.448)	(0.014)	(0.005)	(0.783)	(0.495)
L1. LIQUIDITY	0.000	8.720	-0.005	-0.000	-0.000*	-0.022*	-0.031***
	(0.001)	(6.045)	(0.007)	(0.000)	(0.000)	(0.013)	(0.008)
L1.ROA	-0.068**	-771.757***	-0.466*	-0.019**	0.013***	-1.420***	-1.310***
	(0.027)	(203.058)	(0.244)	(0.008)	(0.003)	(0.427)	(0.269)
L1.EQUITY_RATIO	0.005	-26.386	0.237**	0.009***	-0.002	0.026	-0.251**
	(0.010)	(78.193)	(0.094)	(0.003)	(0.001)	(0.164)	(0.104)
L1.NON_INTEREST	0.002*	27.057***	-0.007	-0.000	-0.000**	0.030*	0.039***
	(0.001)	(7.831)	(0.009)	(0.000)	(0.000)	(0.016)	(0.010)
L1.NPL_RATIO	0.010	80.790	-0.105	-0.004*	-0.003***	0.388***	0.299***
	(0.007)	(55.444)	(0.067)	(0.002)	(0.001)	(0.116)	(0.074)
GDP GROWTH	-0.025**	-130.517*	-0.159*	-0.006*	-0.002*	-0.008	-0.137
	(0.010)	(78.376)	(0.094)	(0.003)	(0.001)	(0.165)	(0.104)
INFLATION	-0.003	71.114	0.154	0.003	0.001	-0.169	0.236**
	(0.010)	(79.531)	(0.096)	(0.003)	(0.001)	(0.167)	(0.106)
Observations	2073	2073	2073	2073	2073	2073	2073
Number of banks	238	238	238	238	238	238	238
R-squared	0.766	0.842	0.785	0.761	0.870	0.607	0.729
BANK FE	YES	YES	YES	YES	YES	YES	YES
TIME FE	YES	YES	YES	YES	YES	YES	YES

Instrumental Variable Regression and credit risk (Google Trend)

	First-Stage Regression	Second-Stage Regression	First-Stage Regression	Second-Stage Regression
VARIABLES	**(1)** **Tech_Dev**	**(2)** **NPL_Ratio**	**(3)** **Tech_Dev**	**(4)** **NPL_Ratio**
GoogleTrend	-0.007*** (0.003)		-0.007*** (0.002)	
L1.Tech_Dev		-0.229** (0.096)		-0.238*** (0.094)
Observations	148	148	148	148
R-squared		0.147		0.097
Bank FE	YES	YES	YES	YES
Time FE	YES	YES		
Country#Time FE			YES	YES
Sargan statistic		exactly identified		exactly identified
F-test of excluded instruments (p-value)	6.85 (0.010)			

Instrumental Variable Regression and credit risk (Number of Fintechs)

	First-Stage Regression	Second-Stage Regression	First-Stage Regression	Second-Stage Regression
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
	Tech_Dev	**NPL_Ratio**	**Tech_Dev**	**NPL_Ratio**
Fintech_Num	0.002***		0.003***	
	0.000		(0.000)	
L1.Tech_Dev		-0.021**		-0.023**
		(0.011)		(0.011)
Observations	392	392	392	392
R-squared		0.147		0.097
Bank FE	YES	YES	YES	YES
Time FE	YES	YES		
Country#Time FE			YES	YES
Sargan statistic		exactly identified		exactly identified
F-test of excluded instruments (p-value)	36.81 (0.000)		36.33 (0.000)	

Conclusions

- Banks mainly rely on back-office solutions which improve banks access to data and infromation processing.
- We find that banks with more Fintech solutions tend to have lower levels of NPLs and that this effect increases with time and the number of adopted solutions.
- We also found that Fintech solutions in the banking sector decrease systemic risk, with digital payment solutions having the most significant impact.
- Reliance on external providers increase global risk if banks share the same technology.
- These results are robust to different technological measures, sample selection, and systemic risk indicators.

Navigating the Digital Frontier: Unraveling the Impact of Bank Technological Development on Credit and Systemic Risks

Abstract

This study examines the impact of digital technology adoption on individual bank credit and systemic risks within the banking sector. Using a dataset of 363 European and U.S. banks from 2009 to 2019, we find that increased technological adoption is associated with significant reductions in non-performing loan ratios and systemic risk. Specifically, technologically advanced banks experience a 1.8–1.9 percentage point reduction in their NPL ratios compared to less technologically developed banks, driven by improved informational efficiency and enhanced credit risk assessment. Furthermore, we find that digitalized banks exhibit lower synchronicity across risk measures, which collectively translates into an average reduction of $3 billion USD in SRISK per additional technology adopted. However, reliance on shared technology seems to homogenize decision-making processes, increasing the SRISK. No evidence suggests sensitivity to sample selection, differences in business models, or variations in technology variables.

Keywords: bank digitalization, credit risk, systemic risk, technological innovation, financial stability.

JEL codes: G21, G23, G32, O33, L13

1. Introduction

In an era defined by unprecedented technological advancements, financial institutions across the globe are increasingly channeling substantial resources into digital innovation. In 2023, global technology investments exceeded USD 4 trillion, with Fintech and DeepTech accounting for more than USD 330 billion as early (Statista, 2024). This trend is particularly evident in the banking sector, where technology expenditures surged by 38% between 2013 and 2022. By 2022, information technology (IT) costs accounted for 10.6% of banks' revenues and 20% of their total operating expenses, reflecting multibillion-dollar commitments to digital transformation (McKinsey, 2024). While the operational benefits of digitalization—such as faster processing, automation, and operational efficiency—are widely acknowledged, its implications for financial stability remain underexplored. Specifically, there is limited empirical understanding of how bank digitalization impacts its credit risk at the individual level and systemic risk at the sector-wide level. Consequently, our study addresses this gap by investigating the role of bank technological development on non-performing loans (NPLs) and systemic risk.

On the one hand, technological innovations have been shown to significantly enhance informational efficiency by granting access to a broader and more diverse range of data (Berg et al., 2020; Jagtiani & Lemieux, 2019). This, in turn, translates into the reduction of information asymmetry, and improves the access to credit, especially for the previously constrained applicants (Bazarbash, 2019; Beaumont et al., 2022; Ghosh et al., 2021; Ouyang, 2022; Palladino, 2021). However, growing reliance on hard data in credit decision-making may come at the expense of soft data traditionally collected by banks through relationship-based lending. Soft data, including qualitative insights gained through personal interactions and borrower relationships, has historically played a crucial role in assessing creditworthiness, particularly in the contexts of economic strain or sector-specific risk challenges (Liberti & Petersen, 2019). Unlike standardized hard data, soft data allows more specifically to capture borrower behavior and resilience that cannot be easily quantified. For instance, during periods of financial stress, soft data has proven uniquely valuable in identifying borrower adaptability, trustworthiness, and other qualitative factors that are critical for informed lending decisions but are often missed by algorithm-driven approaches (Liberti & Petersen, 2019). Moreover, recent case studies of banks incurring significant losses from automated lending models highlight a critical limitation of hard-data-driven credit verification. While algorithmic models may enhance informational efficiency and scalability, they remain vulnerable to fraud and data manipulation, as automated procedures often rely on data from document-based verification that can be also artificially inflated or falsified. In only 2023 the European banks has incurred over EUR 900 millions of losses in the automated lending decisions.[1] Therefore, there might exist discrepancies between digital credit assessment which may improve quantitative risk scoring, however, it does not fully mitigate risks arising from qualitative misrepresentation.

On the other hand, even if more hard data allows banks to reduce the information asymmetries, and hence some sort of bank credit risk, it can still affect the systemic risk if NPL levels become more correlated across institutions. Brunnermeier & Pedersen (2009), Cannas et al. (2015), Zedda & Cannas (2020) highlight that even small losses can have outsized systemic effects due to their cumulative impact across the financial system.

This technological interconnectedness in the credit risk between institutions could arise from at least two critical factors. First, the reliance on hard data and algorithmic decision-making can increase correlation among banks when similar information is utilized and uniform decision-making patterns are adopted (Akter et al., 2022; European Union, 2019; Khandani et al., 2010). Such a situation may happen as the trend in the availability and usage of the hard data is widely observable. For example, in the United States, TransUnion collaborates with Spring Labs and Quadrata to facilitate credit data sharing via blockchain technology, allowing for more secure and efficient assessments. Similarly, in Europe, Colendi employs decentralized blockchain-based credit scoring platforms to enhance data accessibility and consistency. While alternative sources of data may improve bank individual credit risk assessment, the shared data platforms can increase the correlation in the credit decisions, amplifying systemic interconnectedness. Second, systemic risk may be further heightened by banks' dependence on shared technology providers. Our data reveal that 80% of banks rely on the same technology providers during their technological development. Other anecdotal evidence indicates that concentration in the technology platforms, as cloud is currently 60% (S&P Global, 2021).

In our paper we begin by testing the effect of bank technological development on NPLs. We then proceed to investigate how banks' technological development influences systemic risk. Our analysis begins by examining the synchronicity of risk measures across banks, following the methodology employed by Chan et al. (2013). The authors investigate the extent to which stock prices of individual firms move in tandem with broader market or industry indices what they refer to as stock price synchronicity. Following this approach, we examine the

[1] https://www.eba.europa.eu/sites/default/files/2024-08/465e3044-4773-4e9d-8ca8-b1cd031295fc/EBA_ECB%202024%20Report%20on%20Payment%20Fraud.pdf

synchronicity of individual bank NPLs and Tier 1 capital measures across highly digitalized and not-at-all digitalized or less digitalized banks. This analysis enables us to identify potential correlations in risk measures between these groups of banks, shedding light on the systemic implications of digitalization in the banking sector.

Building on this foundation, we empirically test the relationship between bank technological development and systemic risk, utilizing the widely recognized SRISK measure along with its components. SRISK has been extensively employed to identify the determinants of systemic banking crises, providing a robust framework for assessing systemic vulnerabilities in the banking sector (Adrian & Brunnermeier, 2016; Brownlees & Engle, 2017; Brunnermeier & Cheridito, 2019). To enhance our analysis, we investigate which technological solution adopted by a bank contributes most significantly to the reduction of systemic risk. Specifically, we evaluate the role of key technologies adopted by banks, among others, such as data platforms, investment platforms, online lending platforms, financial product platforms, electronic payment systems, and blockchain solutions. Each of these technologies has the potential to improve banks' informational efficiency by providing access to additional, high-quality data or by processing this data more efficiently. At the same time, the hardening of information increases the risk of greater availability of these data on the market (Liberti & Petersen, 2019), and thus a greater synchronicity in the decision-making process among different banks. Therefore, in our approach we aim to determine whether there is any correlation between the type of a technology adopted by a bank and our SRISK measures.

Furthermore, to enhance our analysis, we examine the influence of the source of technology adoption and the implications of shared reliance on technology providers for systemic risk in the banking sector. To this end, we collected data on whether a bank's technology was developed in-house or sourced externally. This would allow us to test whether the purchase of the technology might be more likely to be correlated with the systemic risk due to the potential similarities in banks' operation. Additionally, we measure the extent to which technological solutions originate from the same providers, enabling us to calculate a concentration metric for technology providers offering similar solutions to multiple banks. This allows us to evaluate whether the sharing of technologies across banks is associated with increased systemic risk, again, potentially due to similarities in decision-making patterns arising from shared data sources or modeling frameworks (Akter et al., 2022; Bartlett et al., 2022).

To address our research questions, we construct a comprehensive dataset covering 363 banks from Europe and the United States over the period 2009 to 2019. This dataset includes 63 large banks for which we gathered granular, annual data on specific technological solutions each bank adopted. These data were sourced from commercial databases, including Crunchbase and CB Insights, and were further augmented through web-scraping of banks' social media profiles, financial reports, and press releases to capture the type, nature, and timing of each technological adoption. For the broader sample of 363 banks, we use the value of intangible assets to capture the level of bank technological development, providing additional robustness to our results technological measure.

In our study the main endogeneity issue relates to the link between bank technology adoption and credit losses while to a lesser extent the endogeneity relates to the systemic risk. For example, banks anticipating higher credit risk or expecting greater profitability may be more inclined to adopt new technologies to mitigate these risks, creating a reverse causality issue. Additionally, banks with stronger financial positions often have greater resources to invest in digital advancements, potentially biasing the observed relationship between digitalization and credit risk. To mitigate these concerns, we employ several econometric strategies. First, we anchor our primary measure of technology adoption to observable technological implementations rather than self-reported data, reducing the risk of bias stemming from internal risk assessments. Second, we implement a dynamic and staggered two-way fixed effects difference-in-differences (TWFE DiD) approach, which leverages variations in the timing and intensity of technology adoption across banks to isolate the causal impact of digitalization on credit risk. Third, to further strengthen causal inference, we employ an instrumental variable (IV) approach, using a Google Trends-based digitalization index and the number of fintech firms in a bank's headquarters country as instruments, controlling at the same time for a country-time fixed effect interaction. The Google Trends index captures consumer interactions with banks' digital services and is plausibly exogenous to banks' internal credit risk policies, while the presence of fintech firms exerts external competitive pressure on bank digitalization rather than being a direct response to a bank's credit risk profile. Finally, we complement our analysis with Propensity Score Matching (PSM), ensuring that digitally advanced banks are compared to less digitalized counterparts with similar pre-treatment financial characteristics. This approach controls for potential self-selection biases and strengthens our ability to attribute observed effects to digitalization rather than pre-existing differences in business models.

The results of our empirical analysis prove the premise that banks with higher levels of technological adoption experience lower NPL ratios. This finding is robust across a range of model specifications, including standard, dynamic, and staggered DiD regressions, which allow us to capture both immediate and delayed effects of technology on bank credit risk.

Specifically, our analysis reveals that technologically advanced banks experience a reduction in their NPL ratios by approximately 1.8 to 1.9 percentage points relative to control banks following the treatment period. Furthermore, during the peak year of bank technological development in our sample, we observe that banks with the highest levels of technological advancement exhibited NPL ratios that were nearly 6 percentage points lower, equivalent to approximately 33% of the standard deviation. These findings document that bank technological development enhances banks' credit risk assessment by reducing information frictions, and improving the informational efficiency, which seems to translate into lower credit risk.

Our results from the second stream of analysis reveal that bank technological development significantly reduces systemic risk, with each additional technology adoption lowering SRISK by approximately $3 billion USD, pointing toward a role of banking technology in promoting the diversification in the system. This impact is both statistically and economically meaningful, especially when compared to the peak systemic risk of $1.1 trillion USD during the 2009 financial crisis (Huang et al., 2009).

Importantly, our results reveal that the impact of technological adoption on systemic risk varies significantly by the type of technology implemented by a bank. Specifically, we find that blockchain, data platforms, investment platforms, and electronic payment systems adopted by banks are associated with a significant reduction in SRISK. This suggests that these technologies enable banks to leverage unique and high-quality information in their customer assessments, which does not seem to correlate with other decisions. However, an opposite effect we find when banks shared the technology across themselves. Then, our regression results indicate that bank sharing the same technologies increases the SRISK, pointing toward a more standardized decision-making patterns, and increase decision interdependencies. Thus, our findings suggest that while bank digital transformation enhances financial stability by mitigating both idiosyncratic and systemic risks, the concentration of technology providers introduces new channels of systemic interconnectedness. All robustness checks including the IV regressions confirm our baseline regression results.

The paper is organized as follows: Section 2 discusses the contribution of the paper to the existing academic literature, Section 3 discusses the data while Section 4 the methodology. Section 5 provides the details on the empirical findings, and Section 5 concludes with policy implications.

2. Literature contribution

Our study provides the literature contribution to the three stream of literature. First, we contribute to the literature on measures of bank technological development. Previous studies often rely on either broad or very specific measures—such as total IT spending, the number of computers, number of bank employees or branches, loan processing times, or the mere existence of digital banking channels like mobile banking apps, bank web pages, or online banking services (see, for example, Bloom et al., 2012, 2014; Brynjolfsson, 1994; D'Andrea & Limodio, 2023; Ferri et al., 2019; Garg et al., 2021; Martinez Peria et al., 2022; Pierri & Timmer, 2022; Timmer et al., 2021). While these indicators provide an initial understanding of a bank's digital adoption, they fail to capture the multidimensional nature of bank digitalization, which might affect different types of banks' operations in various ways. To this extent, we've tried to capture the full level of bank technological development to understand how the bank digitalization process internally performs and which bank businesses it affects. Moreover, our approach goes further than just this as it also tracks the source of bank digitalization - whether driven in-house or externally sourced- each of which can have distinct implications for both individual bank operations and the broader financial system. For instance, internally developed technologies may align closely with a bank's strategic priorities, while externally sourced solutions might introduce standardization or dependency risks that affect systemic dynamics. Indeed, our findings reveal that the impact of technology on banking risks is far from uniform, and both the type and source of technological adoption play critical roles in influencing in this effect. By identifying these distinctions, our study addresses a gap in the literature related to the heterogeneity of technological impacts in banking.

Second, we contribute to the academic literature by examining the role of hard data in credit risk assessment and its impact on reducing NPLs within the banking sector. Prior research demonstrates that alternative data sources, such as transaction histories and behavioral analytics, enhance credit assessments by mitigating information asymmetries (Bazarbash, 2019; Berg et al., 2020; Cornelli et al., 2024; Gambacorta et al., 2020; Ghosh et al., 2021; Y. Huang et al., 2021; Jagtiani & Lemieux, 2019; Palladino, 2021). However, much of this research is based on findings from fintech firms, which operate in a less restrictive environment that allows for greater flexibility in utilizing diverse and unconventional data sources (Feyen et al., 2021). This regulatory latitude enables fintechs to innovate in credit evaluation by incorporating alternative data, such as social media activity, utility payments, and behavioral analytics, to enhance informational efficiency and reduce information asymmetries, often resulting in a more precise credit risk assessment. In contrast, traditional banks face stricter regulatory frameworks that limit the scope of data they can leverage, constraining their ability to adopt similarly expansive approaches. Therefore, a trend in the banking sector of giving up soft data and replacing it with more standardized, algorithm-driven hard data raises concerns about banks' ability to capture important risk factors and assess borrower characteristics comprehensively (Liberti & Petersen, 2019). A few existing studies have examined the broader role of IT in banking resilience, particularly during financial crises. For instance, Pierri & Timmer (2022) find that higher IT adoption before the Global Financial Crisis enabled banks to originate higher-quality loans and maintain lower NPL ratios during the crisis, suggesting that technology enhances credit screening capabilities. However, their measure of IT adoption—based on the number of computers and employees per branch—does not necessarily capture the nature of technological adoption occurring today. For example, while a higher number of computers may indicate improved data storage and analysis, lending decisions could still be driven by relationship-based banking. This combination of soft and hard data may enhance credit screening, but it does not necessarily imply that full digitalization and automation in lending decisions would yield the same results. Similarly, Kwan et al. (2023) highlight that banks with stronger IT capabilities adapted more effectively to the COVID-19 pandemic by shifting to digital operations and maintaining their lending activity. However, their study primarily focuses on the role of bank IT systems in lending and customer care, without fully exploring the implications for credit risk. A few existing studies have examined the broader role of IT in banking resilience, particularly during financial crises. For instance, Pierri and Timmer (2022) find that higher IT adoption before the Global Financial Crisis enabled banks to originate higher-quality loans and maintain lower NPL ratios during financial crisis, suggesting that technology enhances credit screening capabilities. However, their measure of IT adoption—based on the number of computers and employees per branch—does not necessarily reflect the nature of technological adoption occurring today. For example, a higher number of computers could be related to a better data storage and analysis, however, the decision on bank lending could still rely on relationship. This combination of soft and hard data, indeed could lead to an enhanced screening, however, does not necessary mean that full bank digitalization and automatization in the decisions could lead to the same results.

Similarly, Kwan et al. (2023) highlight that banks with stronger IT capabilities adapted more effectively to the COVID-19 pandemic, shifting to digital operations and maintaining their lending activity. Yet, their study primarily investigates the role of bank IT systems on bank lending growth. Our study advances this body of research by providing empirical evidence on how the shift toward "hardening" information, mostly done through specific technology influences credit risk management within banks, and as a result its impact on NPLs. Our regression results confirm that hardening of information and automatization in bank lending decisions does not negatively affect bank risk. In turn, our findings prove that banks employing more advanced technological solutions experience significant reductions in NPL ratios, suggesting that technology seems to improve the accuracy and timeliness of credit risk assessments, reducing bank risk.

Furthermore, our research makes a significant contribution to the literature on systemic risk by examining how bank-specific digitalization strategies interact with overall financial stability. This work advances the understanding of systemic vulnerabilities by integrating insights from the systemic risk arising from network effects within the banking sector. While a substantial body of research has analyzed the role of network effects within the banking sector—particularly focusing on interbank exposures, liquidity flows, common asset exposures, and counterparty risks (Acharya et al., 2017; Allen & Gale, 2000; Brunnermeier & Pedersen, 2009; Freixas et al., 2000; Georg, 2013), our study broadens this perspective by assessing network effects in the context of technology providers and its concentration. Our findings indicate that technological concentration in the banking sector may lead to the standardization of the decisions through shared platforms, and thus may create new source of systemic risk channel in the banking sector.

3. Data

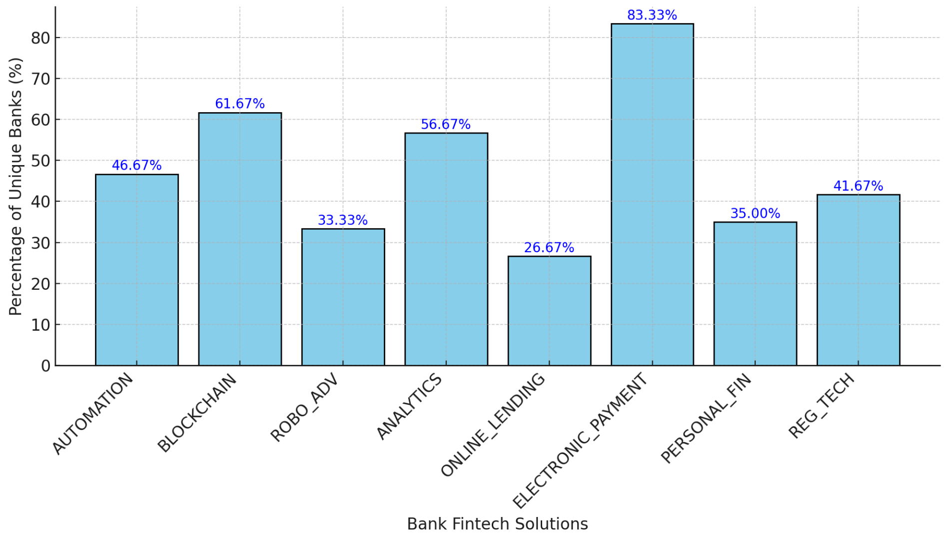
3.1. Digitalization Data

To comprehensively assess the impact of technological development on both idiosyncratic (individual bank) and systemic (sector-wide) risks, we leverage a unique dataset covering the 63 largest European and U.S. banks from 2008 to 2019. This dataset provides granular information on the adoption of a diverse range of technological solutions adopted by banks, capturing advancements across both front-office and back-office banking functions. Our primary data sources include Crunchbase and CB Insights (incorporating Aberdeen Technology data), which provide granular information on banks' technological implementations. To enrich and validate this dataset, we employed data-mining techniques and supplemented the information by manually collecting data on banks’ announcements regarding technology implementations. These announcements were gathered from sources such as banks' official social media (Twitter, Linkedin, Facebook, Instagram) accounts, financial reports, and press releases.

Consequently, we were able to identify the following types of bank technological solutions such as: automation (*Automation*), data platforms (*Analytics*), investment platforms (*Robo_Adv*), online lending platforms (*Online_Lending*), customer financial product platform (*Personal_Fin*), existence of blockchain technology (*Blockchain*), electronic payment solutions (*Electronic_Payment*), and regulatory technology (*Reg_Tech*). To measure overall technological development of a bank, we construct a composite index, *Tech_Dev*, which aggregates the cumulative number of technological solutions each bank has adopted each year. This aggregate measure provides a holistic view of a bank's digital maturity, capturing the extent of its technological progress relative to its peers.

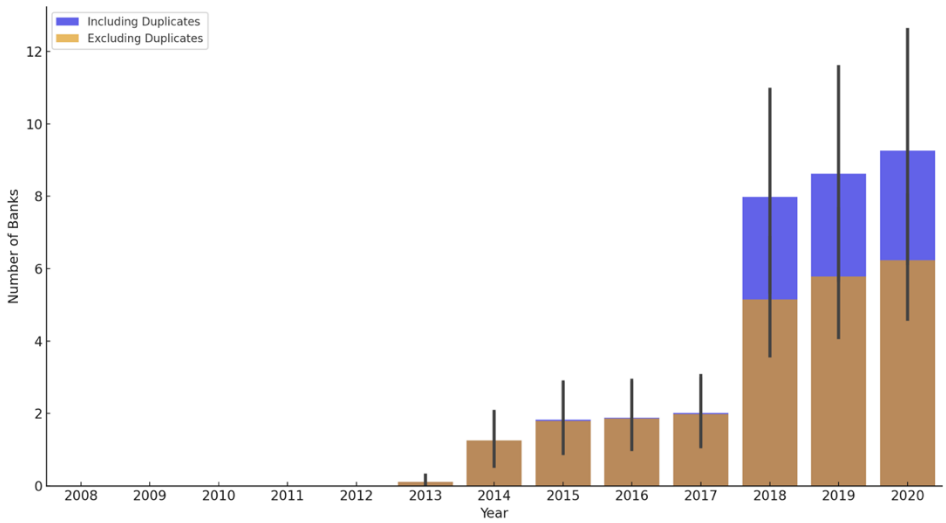
Figure 1 illustrates the heterogeneities in technological adoption patterns across banks while **Figure 2** presents interesting insights into the source of banks' technological adoption.

Figure 1: Percentage usage of bank technological solutions



Source: Own data

Figure 2: Scale of banks using the same technology providers over time
The illustration presents the overall number of banks using the same. Technology provider. The difference between the blue bars (including duplicates) and the orange bars (excluding duplicates) highlights the level of duplication defined as number of banks using multiple solutions from the same provider.



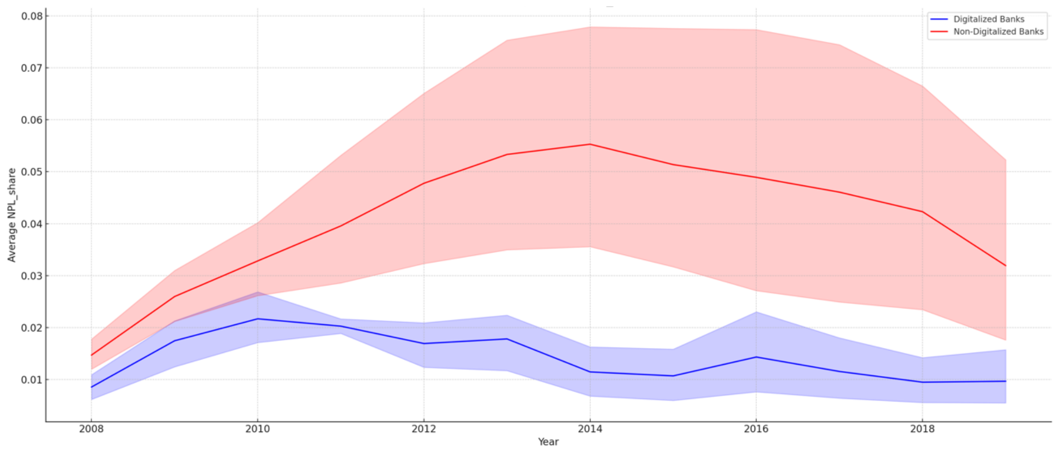
Source: Own data

The data from **Figure 1** document that electronic payment is the most implemented innovation, accounting for 83% of banks using it. In second and third place are data *Analytics* and *Blockchain* with 57% and 62% of banks adopting these technologies, respectively. *Online_Lending* and *Robo_Adv* had the lowest adoption rates among the banks in our sample. These findings are consistent with the results of Lerner et al. (2021) who document that payment solutions, cybersecurity, and communication (such as chatbots) are the most common areas for patent filings. Technologies related to retail banking, commercial or investment banking had a smaller share of the number of patents filed. **Figure 2** highlights that the majority of banks rely on external providers for their technology needs, with only 15% developing solutions internally. Over time, especially between 2013 and 2019, we observe a notable increase in banks using the same technology providers, indicating growing concentration and potential systemic risk due to shared technological dependencies. This concentrated reliance on a few dominant technology providers suggests an emerging specialization within the tech market, with firms supplying critical services to major financial institutions. Such concentration could lead to correlated risks, as multiple banks adopt similar technologies, potentially synchronized in data and algorithmic patterns, thus amplifying systemic vulnerability.

3.2. Risk measures

In our paper, we investigate the impact of bank technological development on banking sector risk, including both individual and systemic risk. To measure the bank's idiosyncratic risk, we use the level of bank non-performing loans as a ratio of non-performing loans to total loans (*NPL_Ratio*). Since the 2007-08 financial crisis, NPLs are in the spotlight for both regulators and banks as they have been linked to bank failures and have been often a trigger for economic shocks (Ghosh, 2015; Barseghyan, 2010). **Figure 3** presents the level of bank NPLs over the periods while splitting banks depending on the number of implemented technological solutions.

Figure 3: Trend of NPLs over time between two groups of banks
The trend lines present the development of NPLs over different years for digitalized banks (the number of technological solutions is higher than 4) and for non-digitalized banks (the number of technological solutions is zero).



Source: Own elaboration.

We notice that prior to 2011, NPL levels moved in parallel across both high- and low-digitalized banks, reflecting a period of global financial crisis that affected the entire banking sector, though in different scale. This alignment across banks suggests a uniform response to external economic pressures, as banks during this time had limited technological differentiation.

Post-2011, however, a divergence in NPL levels emerges, with highly digitalized banks showing a notable decrease in NPLs relative to their lower digitalized counterparts. This shift coincides with a broader recovery in the banking sector and the onset of digital transformation, where banks began implementing technologies to enhance credit risk assessment, monitoring, and operational efficiency. The widening gap in NPL levels between the two groups could illustrate the impact of technological adoption on risk management, as more digitalized banks could have been better in mitigate credit risk, which would be in line with the studies that bank technological development due to access to more data and its more enhanced analytics could allow banks to reduce the information frictions, and thus improving the credit risk assessment.

To assess systemic risk, we employ the *SRISK* measure to evaluate each bank's contribution to system-wide financial distress. SRISK quantifies the potential capital shortfall of a bank during a severe market downturn, specifically a 40% market decline over a six-month period, with an assumed prudential capital requirement of 8% for all institutions in the sample (Acharya et al., 2012, 2017; Brownlees & Engle, 2017; Engle et al., 2012). A positive SRISK value indicates that a bank is likely to experience a capital shortfall under these conditions, thereby contributing to systemic risk, whereas a negative SRISK value signifies a capital surplus, implying resilience under stress. Therefore, a bank is deemed systemically risky if it faces a capital shortage precisely when the broader financial system is under strain (Acharya et al., 2017). We compute SRISK both in absolute terms, reflecting the capital shortfall in USD, and in relative terms as a percentage contribution to the total positive SRISK of the financial system (*SRISK%)* ((Brownlees & Engle, 2017). The latter metric allows us to gauge the proportional impact of each bank's SRISK on the overall systemic risk profile, facilitating a clearer comparison across institutions in terms of their vulnerability and potential to exacerbate sector-wide distress.

3.3. Other control variables

In our models, we also control for bank observable features which have been documented to impact the bank risk level. More specifically, we include *Size*, defined as the log of a bank total assets (Demirgüç-Kunt & Huizinga, 2010; Wu et al., 2020). We also include TIER1 capital (*TIER1_Ratio*), defined as the ratio of bank equity to total asset. Well-capitalized banks may better absorb economic shocks and are less willing to take risks (Bordo et al., 2016; Morgan, 2002). We also control for liquidity risk *(Liquidity*) using loans to deposits ratio. Excessive liquidity creation could lead to a higher banking sector risk (Fungacova et al., 2021; Zhang et al., 2021). We also control for bank credit activity and business model, with two alternative measures: the share of loans in total assets (*Credit_Activity*), and the share of non-interest income in total income (*Noninterest_Income*). A lower share of loans and a lower share of non-interest income reflect a higher bank involvement in market-based activities (Demirgüç-Kunt & Huizinga, 2010; Bordo et al., 2016). Finally, we also include *ROA* as a measure of bank profitability, defined as net income over the bank total asset. The market may consider more profitable banks more resilient, and hence ROA may be negatively related to systemic risk measures. On the other hand, high profitability may also be a sign of risk-taking, in which case it may be associated with more systemic risk (De Jonghe, 2010). We also include the bank efficiency (*Efficiency*), defined as banks' general costs to income. We expect that less efficient banks are more likely to take on higher risk (Fiordelisi et al., 2011). Finally, macroeconomic factors may also influence banks' risk. Thus, the second set of controls are macroeconomic variables collected from the World Bank Database. We include the annual GDP growth rate (*GDP_Growth*) and inflation (*Inflation*) whose effect on the systemic risk is expected to be negative. We also include banking sector concentration (*Concentration*) which is likely to be correlated with the level of banks individual and systemic risk (Beck et al., 2022). **Table 1** provides the summary statistics for all data used in our analyses. We also provide the definitions of all variables used in our study in the **Appendix in Table A1**.

[Table 1]

4. Methodology

4.1. Difference-in-Difference for Bank technological development and NPLs

To investigate the impact of bank technological innovations on NPL levels, we employ a two-way fixed-effect difference-in-differences regression model. This approach is well-suited to our analysis as it allows us to control for time-invariant unobserved heterogeneity across banks and common shocks over time, addressing potential sources of endogeneity that might bias the relationship between bank technological development and its risk.

Our choice of TWFE DID aligns with recent literature (Baker et al., 2022; Roth et al., 2023), which highlights the robustness of DID models in capturing causal relationships while addressing concerns of endogeneity and omitted variable bias. This method is particularly beneficial in our context, as banks may self-select into adopting technology based on factors that could simultaneously influence their credit risk management. By assigning banks to treated and control groups based on their digital adoption levels, we are able to compare banks with similar pre-treatment characteristics and observe the differential impact of their technological development.

We define the treatment group as being composed of highly technology advanved banks (High_Adopters) if they adopt more than four technological solutions, with the threshold set at the median for the sample period. We then define a control group as banks with no adopted technological solutions (Non_Digitalized). By establishing the control group as non-digitalized banks, we maintain a stable comparison group across time, which helps mitigate potential biases from heterogeneous treatment effects, stemming from not-yet digitalized banks (Roth et al. 2023). For robustness, we define an alternative treatment group that includes banks with any level of technological adoption and compare to non-digitalized banks. Additionally, in the robustness we conduct a quantile analysis to examine different levels of bank digitalization and compare them to not-yet-digitalized banks. This alternative approach tests the sensitivity of our results to varying degrees of digitalization within the banking sector.

To identify the appropriate treatment period, we mark 2011 as the start of the digitalization shock, based on both historical and sectoral evidence. The period from 2011 onward saw a convergence of development in Fintech innovations, regulatory changes, and the rapid adoption of such technologies as mobile banking, cloud computing, and big data analytics, representing a shift in strategies toward technological development on the market (Feyen et al., 2021). Our peer analysis from the prior section supports this timing (**Figure 3**), showing a divergence in NPL trends between high and low technologically advanced banks beginning in 2011. By establishing 2011 as the treatment start date, we aim to capture the long-term impact of technology adoption on credit risk while minimizing the likelihood of endogeneity arising from pre-treatment trends. Moreover, in line with recent advances in DID methodology (Baker et al., 2022; Roth et al., 2023), we incorporate dynamic DID to examine the year-by-year effects of bank technological development. By interacting the treatment effect with each year, we can observe how the impact of bank digitalization on NPLs evolves over time, offering a more granular view of the effects and testing the consistency of treatment impacts across years. This approach allows us also to test the effect of parallel trends in the pre-treatment period given our initiated shock.

Furthermore, we extend our analysis by employing staggered DID models. In the staggered DID, banks enter the treatment group dynamically when they reach a high level of technological development (more than four solutions). This approach allows us to control for the gradual and uneven adoption of technology across banks, limiting potential bias from the treatment timing (Roth et al., 2023).

In our model we also control for the unobservable bank characteristics using the bank-fixed effect as well as for time-fixed effects to control for the effects of a business cycle that could have been important during the financial crisis. Additionally, we also add the observable bank characteristics which might have impact the level of bank NPLs, as described in the previous sub-section. Consequently, our empirical models takes either static or dynamic form:

$$\mathbf{NPL\_Ratio}_{it} = \beta_0 + \beta_1 TreatmentYears_t + \beta_2 High\_Adopters_{it} + \beta_3(TreatmentYears*High\_Adopters)_{it} + \beta_3 X_{i-1t} + \beta_4 Z_{jt} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where *i* refers to the bank, *t* to the year. Our outcome variable NPL_Ratio_{it} is defined as a share of non-performing loans to bank total assets at year *t*; TreatmentYears*High_Adopters is our key variable of interest. It is an interaction between the treatment years (or treatment period in a standard DID) and a dummy for being a „High_Adopters" (i.e. having at least 5 adopted technological solutions). X_{it-1} denotes the bank-level variables as described in the previous section while Z_{jt} denotes country and macro-variables. α_i , λ_t are bank-fixed and time-effects. The standard errors are robust and clustered at the bank level to correct for both autocorrelation and heteroscedasticity.

4.2. Bank technological development and systemic risk

To examine the link between banks' technological development and systemic risk we estimate the following model:

$$\mathbf{SRISK}_{it} = \beta_0 + \beta_1 Tech\_Dev_{it} + \beta_2 X_{it-1} + \beta_3 Z_{jt} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (4)$$

SRISK includes systemic risk measures as: *SRISK* and *%SRISK* by bank *i* in time *t*. Z_{jt} includes country variables. The main regressor of interest is $Tech\_Dev_{it}$. It allows us to identify the effect of bank technological development on systemic risk measures. Similarly, as in the previous specifications, we define $Tech\_Dev_{it}$ as a number of solutions adopted by a bank *i* in a given year *t*. Additionally, we also test the effect of the type of technological solutions on systemic risk measures. To this extent, we distinguish Automation, Blockchain, Analytics, Online_Lending, Electronic_Payment, Personal_Fin, Robo_Adv, Reg_Tech and denote one if a bank has adopted a specific solution in time *t*; otherwise, it is zero. This approach allows us to address not only the impact of bank technological development but also the role of specific types of solutions on systemic risk measures.

We also control for the source of the bank technological adoption. To this extent, we distinguish between the in-house development (*In-House*), technology purchases from external technological providers such as Fintechs or DeepTechs (*Investment*), and outsourcing (*Outsourcing*). We control for these effects by including the dummies equaling one for the identified technology adopted by a bank that has been implemented by a specific approach. Otherwise, we assign for such a bank-solution zero. This would allow us to examine whether any source of technological adoption may increase risk due to, for example, more correlated decisions across solution providers. Finally, we also control more explicitly for the same source of technology adoption ($Tech\_Sharing_{it}$) by capturing the number of the same technology providers for each solution with other banks for each period of time.

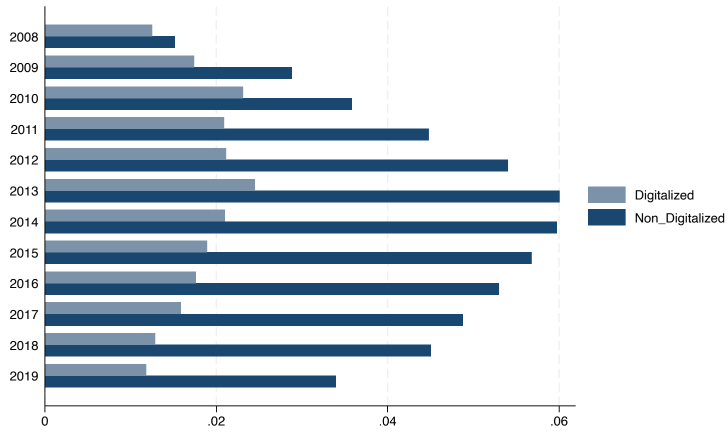
Finally, we also include bank-and-country controls which have been documented as important determinants of systemic risk (Acharya et al., 2017; Huang et al., 2012; Laeven et al., 2016). Additionally, the time-fixed effect controls for the time-variant factors which could also affect the potential relationship between the bank's technological development and risk, for example, better internet access in a given country or better data sharing. Berger & DeYoung (2006) claim that the time-fixed effect is a good measure of the aggregated technological progress over time.

5. Empirical Tests

5.1. Univariate analysis

Before we come to the econometric analysis, we we first establish a few key stylized facts concerning the relationship between digitalization, non-performing loans, and risk co-movement within the banking sector. Specifically, we investigate whether banks that have adopted innovative technological solutions exhibit lower NPL ratios compared to banks without such solutions. For this preliminary analysis, we categorize our sample into two groups: banks with at least one technological solution (Digitized) and those with no technological adoption (Non_Digitized). **Figure 4** illustrates the average NPL ratio for both groups over the sample period.

Figure 4: The average distribution of NPLs among two groups of banks.

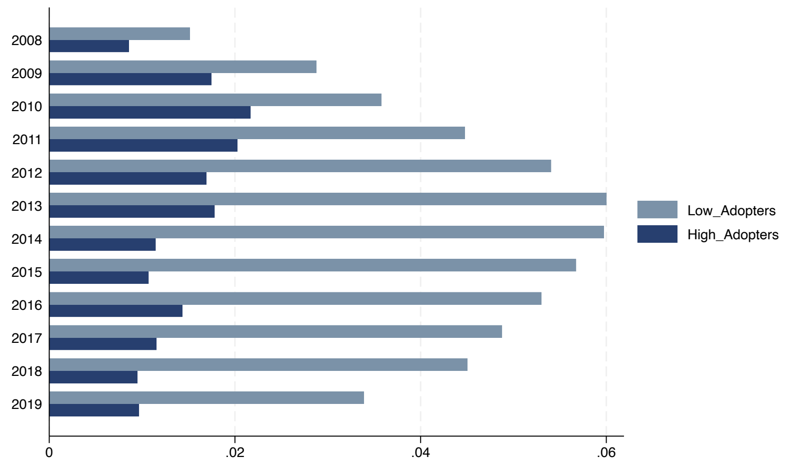


Source: Own estimations

The Figure indicates that digitalized banks generally maintain lower NPL ratios than non-digitalized banks across most years, though the gap varies over time. Before 2010, both groups experience relatively stable NPL ratios with minimal fluctuations. Post-2010, we observe a general trend where digitalized banks maintain lower NPL ratios, with a noticeable dip around 2014. Non-digitalized banks, on the other hand, experience a gradual increase in NPL ratios until about 2014, followed by fluctuations. By 2019, digitalized banks exhibit an NPL ratio that is significantly lower than non-digitalized banks.

To account for potential heterogeneity among digitalized banks, we categorize them into "High_Adopters" (those adopting more than four technological solutions, exceeding the median) and "Low_Adopters" (those adopting fewer than five solutions, below the median). **Figure 5** illustrates the average NPL ratio across these two groups, highlighting the influence of technological intensity on NPL trends.

Figure 5: The average distribution of NPLs among two groups of banks.



Source: Own estimations

During the financial crisis period (2008–2010), both high and low technology adopters experienced an increase in NPL ratios, with High_Adopters showing a slightly less pronounced rise. Following 2010, the trends diverge: high technology adopters display a consistent downward trend in NPL ratios, indicating that more advanced technological adoption may contribute to better credit risk outcomes. In contrast, low technology adopters exhibit a more mixed pattern, with fluctuations in their NPL ratios over time. By the end of the study period in 2019, high technology adopters have achieved significantly lower NPL ratios, approximately one-third of those observed in low technology adopters. This disparity underscores the potential role of intensive technological adoption in enhancing credit risk resilience, providing the potential supporting for our hypothesis that higher levels of bank digitalization may contribute to reduced NPL levels within the banking sector.

Before we empirically assess the effect of bank technology on systemic risk, we are also interested in how bank technological development may affect the correlation across different bank risk measures. To this extent, we conduct a synchronicity analysis, as discussed by Chan et al. (2013). The authors examine how individual company stock market performance depends on aggregated market factors. In the same vein, we are interested in testing how banking sector technological development may affect individual bank risk measures. More specifically, we examine the co-movement between bank NPLs and TIER1– as significant measures of risk in the banking sector (Acharya et al., 2017; Adrian & Brunnermeier, 2016; Ozili, 2020). Higher synchronicity of individual bank risk measures could indicate that small losses in individual banks could amplify a systemic effect if multiple banks are affected. We conduct our regression analysis on two groups of banks: digitalized and non-digitalized, as well as on banks with different levels of technological adoption, measured by the number of solutions. **Figures 6-7** present the regression synchronicity coefficients for NPLs and Tier1 across two groups of banks.

Figure 6: Equity ratio synchronicity among different banks (N=59)

The results have been obtained by regressions: $Financial\ variable_{i,t} = \alpha_i + \sum_{m=1}^{23} \beta_i\ Financial\ variable_{m,t} + \epsilon_{i,t}$ where $Financial\ variable_{i,t}$ indicates equity ratio for a bank i in a year t. We evaluate how bank equity ratio co-moves with equity ratio of the rest of the banks, and $\epsilon_{i,q}$ is the error term. We perform the analysis for two sub-groups: digitalized banks and non-digitalized. We analyze the synchronicity effect between non-digital banks (0 solutions) versus digitalized banks (more than 1 digital solution) as well as within the total number of bank digital solutions.

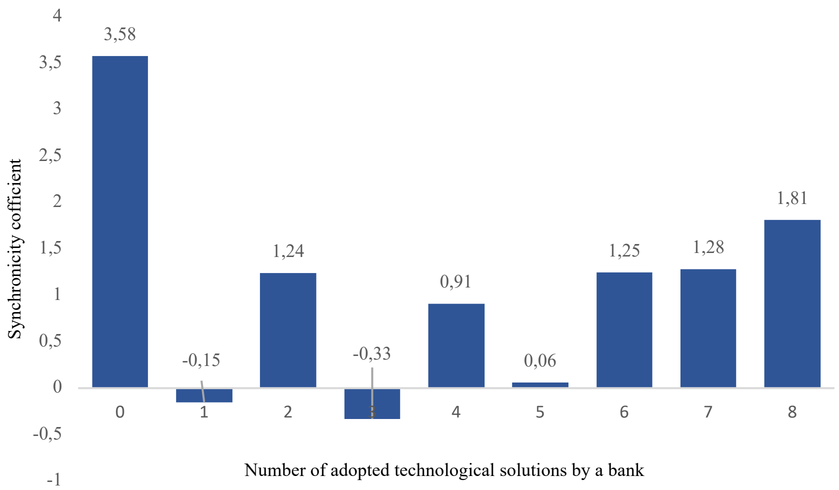
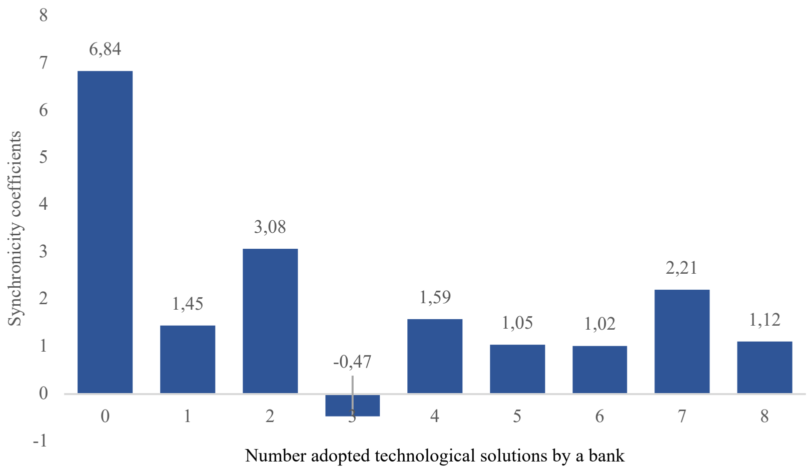


Figure 7: NPLs synchronicity among different banks (N=59)

The results have been obtained by regressions: $Financial\ variable_{i,t} = \alpha_i + \sum_{m=1}^{23} \beta_i\ Financial\ variable_{m,t} + \epsilon_{i,t}$ where $Financial\ variable_{i,t}$ indicates equity ratio for a bank i in a year t. We evaluate how bank NPLs co-moves with NPLs of the rest of the banks, and $\epsilon_{i,q}$ is the error term. We perform the analysis for two sub-groups: digitalized banks and non-digitalized. We analyze the synchronicity effect between non-digital banks (0 solutions) versus digitalized banks (more than 1 digital solution) as well as within the total number of bank digital solutions.



Source: own source

The above results yield several interesting conclusions. Firstly, the findings suggest that non-digitized banks display greater synchronicity in terms of capital changes than digitized banks. The synchronicity coefficient for TIER1 across non-digitized banks is 3.58, whereas, across digitized banks, the highest value is 1.87, with an average of only 0.82 across all digitalized banks. A similar trend is observed in the case of NPLs. The synchronicity coefficient for the NPLs ratio is 6.84 for non-digitized banks, compared to 1.12 for banks with the highest level of digitalization (the average among all digitalized banks is 1.87). The results seem to confirm that technology seems to reduce the correlation in the system across bank NPLs and TIER1. These results may suggest that greater technological development leads to a greater diversification in the system resulting in a lower asset correlation, which may reduce the systemic risk in the banking sector. This seems to be in line with the results of Beck et al. (2022) who document that diversification in the banking system decreases systemic risk.

6. Bank Technological Development and Risk

6.1. Static and Dynamic DID

In this section, we empirically test whether bank technological development affects credit risk resulted in a ratio of bank NPLs. The rationale behind this hypothesis is rooted in the belief that technological advancements, such as data analytics, transactional data, or investment profile, provide banks with access to richer and more accurate information on potential borrowers, increasing timely information efficiency (Berg et al., 2020; P. Ghosh et al., 2021; Jagtiani & Lemieux, 2019; Ouyang, 2022). To empirically test this hypothesis, we utilize both a standard and dynamic DID regression models, which allows us to assess the impact of bank technological development on NPLs, reducing some sort of endogeneity. Especially, the dynamic DID approach is particularly advantageous for addressing endogeneity, as it accounts for potential biases resulting from unobserved, time-varying factors that could affect both the decision to adopt technology and changes in bank NPL levels. The results are presented in **Tables 2 and 3**, respectively.

[Table 2]

[Table 3]

The results of our standard DID regression model provide evidence supporting our hypothesis that bank technological development has a significant impact on reducing banks' credit risk, as measured by the NPLs. Our main variable of interest - the interaction term (High_Adopters*Treatment_Period) – is negative and statistically significant in all specifications, ranging from -0.0180 to -0.0197 across the models, with significance levels mostly at the 5% level. The magnitude of this effect indicates that, all else equal, banks that are more technologically advanced experienced approximately a 1.8 to 1.9 percentage point reduction in their NPLs compared to control banks after the treatment period. This supports our hypothesis that bank technological development improves informational efficiency, which should translate into lower bank NPLs. At the same time, our results prove that hardening the information on a borrower does not negatively impact the banks' risk. In turn, the results show that the adoption of the technology increases the bank informational efficiency suggesting technological innovations can offset some of the limitations associated with reduced reliance on soft data by improving the accuracy and timeliness of credit risk assessments. Furthermore, the lack of significance for the treated indicator (High_Adopters) in the pre-treatment period supports the parallel trends assumption, indicating that treated and control banks followed similar trends in NPL share prior to bank digitalization. This strengthens the validity of our DID approach, as it suggests that the observed reduction in NPL ratio among treated banks seems to be attributed to bank technological development efforts rather than pre-existing differences.

The inclusion of bank controls, additionally to bank-and time-fixed effect, strengthens the robustness of our results by accounting for additional factors that could influence a bank's NPL share. Notably, *Size* and *ROA* are both statistically significant and negative, suggesting that larger banks and those with higher profitability tend to have lower NPL shares. The macroeconomic controls, such as *GDP_Growth* and *Inflation*, are not statistically significant, which may indicate that changes in NPL share are more directly influenced by bank-specific factors than by broader economic conditions during our sample period.

While the standard DID approach captures the immediate impact of bank digitalization, the dynamic DID framework allows us to test the parallel trends assumption across multiple pre-treatment periods. The results from the dynamic DID presented in **Table 3** further confirm our conclusions.

Interestingly, we notice that the coefficients during the financial crisis period (2008-2010) are statistically insignificant, indicating the absence of any pre-trend existence. However, after this period, we observe a change in the effect of our interaction coefficients. For banks that were in the treated group and adopted technological solutions after 2010, we notice a decrease in the level of NPLs. The effect is especially noticeable immediately after 2010. More importantly, the effect remains negative in subsequent years. The statistical significance of the regression coefficients supports the impact of banks' technological development, with most of the coefficients being significant at a one or five percent significance level. The effect is relatively stable across the years, varying between -0.023 and -0.035, with the highest of -0.064 in 2019, when bank technological development in our sample became the most pronounced. These findings suggest that higher levels of bank technological development, achieved through the implementation of more technological solutions, can help banks improve the informational efficiency, thereby managing their credit risk more carefully, resulting in a reduction of NPLs. These results support the theoretical framework that emphasizes the role of digital transformation in enhancing informational efficiency and reducing bank losses.

6.2. Staggered DID

In this sub-section, we employ a staggered DID model to enhance our analysis of bank technological development on credit losses. Unlike standard and dynamic DID models, the staggered DID approach is well-suited for contexts where banks adopt digitalization at different times, allowing for a more precise estimation by accounting for heterogeneous treatment timings. By explicitly modeling the staggered adoption, we can also test our results against the chosen the timing of our chosen “shock”. **Table 4** provides the regression results for staggered DID.

[Table 4]

The regression results provide an interesting picture. Firstly, they reinforce the findings from our previous estimations, documenting that bank technological development improves the information efficiency, and thus leads to the reduction of NPLs. We observe that the coefficients on the interaction variable are statistically significant, and the estimates remain stable across the various specifications, ranging between -0.024 and -0.020 which are in a very similar range as our effects from our previous DID models. Importantly, our regressions using the staggered DID approach also prove that our results on bank technological development and NPLs are unlikely to be biased by the simultaneous development of bank technology and NPLs.

6.3. Bank Digitalization and Systemic Risk

The results of our previous regressions, presented in the earlier sub-section, suggest that bank technological development reduces credit risk at the individual bank level. However, this does not imply that the aggregate systemic risk in the banking system necessarily declines. As Brunnermeier & Pedersen (2009), Cannas et al. (2015), Zedda & Cannas (2020) emphasize, even small losses can magnify systemic effects if they propagate across multiple interconnected banks. Such effects are particularly pronounced in systems where institutions exhibit similar risk exposures. In this section, we extend our analysis to evaluate the relationship between bank technological development and systemic risk, using SRISK as the primary measure while controlling for other relevant factors.

[Table 5]

Table 5 presents the regression results for the impact of technological development on systemic risk, measured both as an absolute value (Column 1) and as a percentage (Column 2). The coefficients for Tech_Dev are negative and statistically significant across both specifications, demonstrating that technological development by banks is associated with a notable reduction in systemic risk. Specifically, each additional technological solution adopted by a bank corresponds to a reduction in systemic risk by approximately $3 billion USD. This reduction is economically meaningful, especially when compared to the peak systemic risk level of $1.1 trillion USD observed in March 2009 (Huang et al., 2020). Moreover, technological adoption reduces a bank's systemic risk share by 0.185 percentage points. These results align with our synchronicity analysis, which reveals that technological development reduces co-movement among key risk indicators, such as TIER1 and NPL_Ratio, suggesting that bank digitalization seems to lead to specialization, promoting the sector diversification.

One of the explanations for these findings could be that that bank technological development enables banks to adopt more specialized strategies, tailoring their decision-making processes to specific clients or market segments. This would be in line with the view of bank specialization, reducing the correlated risk exposures across banks, as documented by Beck et al. (2022).

To further understand these dynamics, we evaluate the differential impacts of specific technological solutions on systemic risk, as shown in **Table 6**. Columns (1)–(6) report the coefficients for various technological innovations adopted by banks, including *Automation,* *Blockchain, Analytics, Online_Lending, Electronic_Payment, Robo_Adv, Personal_Fin,* and *Reg_Tech.* We argue that some of these technologies may enhance similar decision patterns or facilitate data sharing, which could lead to standardized decision-making processes across banks. For example, blockchain may enhance the data sharing which should be visible in a more correlated exposure of banks relying on data coming from blockchain transactions. Electronic_Payment or Robo_Adv might also increase the correlated exposure if banks use the data coming from these technologies in a similar way for their decision-making processes.

[Table 6]

The regression results in **Table 6** support our hypotheses, demonstrating that specific technological innovations, as *Blockchain***,** *Robo_Adv***,** *Analytics*, and *Electronic_Payment*, have statistically significant and negative impacts on SRISK. These findings seem to suggest that these technologies give banks the access to data, however, the way the banks use these data seem to be different, reducing the effect on systemic risk in this sector. For example, banks may tailor their decision patterns to target specific client profiles or market segments, thereby mitigating the homogeneity in credit exposures, despite reliance on similar data types. Among these, *Electronic_Payment* demonstrates the most substantial economic effect, consistent with findings by Ghosh et al. (2021) and Ouyang (2022), which point toward an importance of payment data in reducing information asymmetries, and increasing the access to credit for the so-far constrained borrowers. Other solutions exhibit less statistically significant effects on SRISK, suggesting that these technologies primarily enhance operational efficiency or ensure regulatory compliance, rather than directly influencing banks' decision-making processes.

6.4.Technological Providers and Bank Systemic Risk

Systemic risk in the banking sector can be exacerbated when banks using algorithmic decision-making rely on technological solutions from external providers. In such cases, algorithms may draw on similar data sources and modeling patterns, leading to convergence in asset allocation strategies and, consequently, resulting in higher correlations in risk exposures across the system. Although we lack direct data on the mechanisms behind decision-making patterns, we do have information on the source of technology adoption for each bank. This enables us to link banks with their respective technology providers for each implemented solution. Therefore, we approximate that banks relying on the same technology provider may exhibit similarities in data usage or decision patterns, which could result in correlated decisions and increased systemic risk. This expectation aligns with the theoretical framework of FBS (2019), which posits that external technology providers, such as Fintech or DeepTech companies, often rely on shared data and algorithms to design their solutions. Consequently, banks heavily dependent on external providers may demonstrate higher systemic interconnectedness, potentially amplifying systemic vulnerabilities than banks more exposed to the technology developed in-house.

To test the effect of bank source of technology development on systemic risk, we classify banks' technology adoption sources into three categories: in-house development (*In-House*), purchase (*Purchase*), and outsourcing (*Outsourcing*). We create binary variables for each category, assigning a value of one if a bank adopts a specific technological solution from a particular source in a given year, and zero otherwise. Furthermore, we introduce an interaction term between a bank's technological development (Tech_Dev) and the source of technology adoption to examine whether the impact on systemic risk varies with its source. Our hypothesis posits that purchased technology solutions may lead to more correlated risk-taking across banks due to some similarities in the decision processes, thereby increasing systemic risk. The regression results are presented in **Table 7**.

[Table 7]

The regression results in **Tables 7** provide interesting relationship between technology adoption sources and SRISK in the banking sector. Contrary to our initial hypothesis, the results indicate that banks purchasing technological solutions exhibit a negative association with SRISK, suggesting a reduction in systemic risk by nearly seven percentage points relative to other development methods. This finding implies that banks may customize purchased technologies to meet their unique needs, enabling them to diversify their product offerings and customer segments, putting a reducing effect on SRISK as part of the sector diversification. These results are consistent with our earlier findings, which highlight the role of technological development in reducing systemic vulnerabilities. Importantly, other variables associated with technology adoption, such as outsourcing or in-house development, do not show a statistically significant relationship with SRISK.

To further investigate whether interdependencies in risk-taking arise from shared technology providers, we introduce a new variable, Tech_Sharing, which captures the number of common technology providers a bank shares with other banks in a given year. This time-varying variable accounts for the evolving nature of technological development and adoption. We hypothesize that when a higher number of banks rely on the same provider, systemic risk increases due to the emergence of similar decision patterns across institutions. **Table 8** provide the regression results.

[Table 8]

The regression results in **Table 8** support this hypothesis. The positive and statistically significant coefficient on Tech_Sharing suggests that reliance on shared technology providers amplifies systemic risk. Specifically, the findings indicate that banks using identical technological solutions from the same provider may adopt similar algorithms and data-driven frameworks, resulting in standardized risk management and asset allocation decisions. These similarities increase interdependencies across banks, intensifying systemic vulnerabilities within the financial sector.

7. Robustness Check

In this Section, we aim to provide the robustness of our analyses by redefining the bank's technological measures, sample selection, and potential endogeneity concerns.

7.1. Different specifications of the DID

In this section, we conduct a robustness analysis by applying a more traditional DID framework to validate the stability and reliability of our findings. A key concern with our DID specification might be the definition of treatment banks as High_Adopters. By setting a fixed threshold, we risk excluding banks with fewer than five adoptions, which might raise concern regarding the the arbitrary cutoff. Moreover, the staggered DID approach has faced criticism for potentially introducing bias when a large number of fixed effects are included in the model (Baker et al., 2022; Callaway & Sant'Anna, 2021).

To address these concerns, we adopt alternative definitions of treatment groups that vary by the level of technological development (i.e., the number of technological solutions adopted) rather than relying on a single median-based threshold. Specifically, we categorize banks into different treatment groups based on the number of technological solutions they have implemented, creating three groups: banks with one to two solutions, banks with three to four solutions, and banks with five to six solutions. In this way we create a heterogenous group of banks based on different the number of technological solutions what allows us to test the potential bias related to specific banks (for example, banks which decided to rely on specific solution or types of solutions). The control group is defined as non-digitalized banks. This alternative grouping approach allows us to examine whether treatment effects are robust across varying levels of technological intensity, providing a more detailed understanding of how technology adoption impacts bank NPLs across different levels of technology adoption. We estimate our model using the dynamic DID, where we interact each treatment group with specific years, capturing the temporal dynamics of technological adoption. This setup allows us to observe how treatment effects evolve over time and across different levels of bank technology adoption. The results, presented in **Figures A1–A3** in the **Appendix**, and illustrate the estimated coefficients and 90% and 95% confidence intervals for each interaction term across years.

For banks adopting only one or two digital solutions, we observe a slight decline in NPL ratios post-2010. However, this effect is neither statistically nor economically significant, as indicated by wide confidence intervals that frequently include zero. These results imply that minimal adoption of digital technologies does not significantly reduce bank NPLs. This outcome aligns with our hypothesis that limited digital investments offer restricted improvements, and thus do not effectively reduce NPL ratios. In the group of banks adopting three to four digital solutions, we observe a moderate decrease in NPL ratios, particularly between 2012 and 2016. Although the effect is more pronounced than in the low-adoption group, the reduction remains inconsistent across years. These findings suggest that a moderate level of bank digitalization begins to yield benefits in managing credit risk, but the improvements are less stable and weaker than those observed at higher adoption levels. This result underscores the importance of a higher digitalization, as partial adoption may provide some benefits but does not offer a robust or consistent reduction in NPL ratios. Finally, the most substantial and statistically significant reduction in NPL ratios is observed among banks that have adopted five to six digital solutions. For these banks, the effect on NPL ratios is consistent and significant across years, with narrower confidence intervals that remain below zero. This pattern indicates that a critical mass of technological development is essential to achieve meaningful improvements in credit risk management to affect the NPLs. Our findings suggest that banks with higher levels of digital adoption benefit from more a greater informational efficiency, which translates into a reduction of credit risk.

7.4. Endogeneity Concerns

7.4.1. Alternative measures of bank technological development

To further validate our findings, we conduct a robustness check by examining alternative measures of bank technological development that are prevalent in the literature. Specifically, we utilize the share of intangible assets (excluding goodwill) to total bank assets, denoted as *Intangible_Asset*, as an alternative proxy for bank digitalization. This measure allows us to address potential endogeneity concerns associated with our primary measure—namely, the number of technological solutions adopted by banks—which may be correlated with other bank characteristics that influence bank credit risk. Since the intangible asset is a balance sheet variables accessible from banks' financial statements, we also extend our sample from 63 to 363 banks for which SRISK measures were available to be consistent with our systemic risk analyses.

The use of intangible assets as a proxy for technological advancement is well-supported economically. Intangible assets typically include patents, proprietary technologies, and ongoing research and development investments, which are critical indicators of a bank's technological capabilities. Unlike general IT expenditures, which can vary widely based on operating needs and may reflect routine maintenance rather than innovation, intangible assets often represent more substantive and strategic view of bank management on technology. These assets reflect long-term commitments to digital transformation that are less likely to be directly correlated with day-to-day banking operations, thus providing a more exogenous measure of digitalization that focuses on capacity for innovation and digital development (Lim et al., 2020). Furthermore, because most banks in our sample acquire rather than internally develop technological solutions, *Intangible_Asset* can capture the accumulated value of these digital investments more accurately than other measures, such as IT spending, which may be inconsistently reported or allocated for non-strategic purposes.

Similarly, as in the previous sub-sections, we run the dynamic DID specification where we define the treatment group as banks with *High_Intangible_Asset* ratio at or above the seventy-fifth percentile. This threshold identifies banks that are truly leading in digital adoption, distinguishing them from their less digitalized peers while ensuring the treatment group remains sufficiently big for statistical comparison. By setting this high threshold, we focus on banks with substantial digital capabilities, thus allowing us to isolate the effects of advanced technological development on bank NPLs. **Table 9** presents the regression results.

[Table 9]

Across all specifications, the interaction terms between treatment years and *High_Intangible_Asset* levels show a negative effect on NPL ratios, with statistically significant coefficients emerging after 2010. Notably, we observe that the interaction effects in the pre-treatment period (years prior to 2011) are statistically insignificant, supporting the parallel trends assumption required for a valid DID estimation (Angrist & Pischke, 2008). This finding further validates our DID approach by confirming that differences in NPL ratios between high and low digitalized banks only materialize after a certain level of bank technological development. The impact grows stronger and remains consistently negative from 2011 onward, with the largest effect observed in 2019. This peak suggests that bank technology had progressively matured by this point, resulting in the highest drop in the bank NPLs. These findings support our hypothesis that advanced technological development enhances banks' ability to perform more rigorous credit assessments due to reduction of information frictions. Our findings prove that behavioral and transactional data, in particular, appear to exhibit strong predictive power in assessing credit risk (Angelini et al., 2008; Berg et al., 2020; Gambacorta et al., 2020; Jagtiani & Lemieux, 2019).

7.4.2. Bank Digitalization and Business Models

A key concern in the literature is that banks may self-select into digitalization based on pre-existing business model differences rather than undergoing a fundamental transformation driven by IT adoption. Specifically, banks that are less reliant on lending and generate higher non-interest income may be more inclined to adopt financial technologies, implying that the observed reduction in NPLs could be attributed to a shift away from traditional credit activities rather than improved risk management. Alternatively, banks may adopt the technology to change its business model, which could then result in a reduction of NPLs. To address these concerns, we employ two complementary robustness checks.

First, we examine whether banks that adopt specific technological solutions undergo a fundamental shift in their business models. To this end, we estimate staggered DiD models using interest margin (*Interest_Margin*) and non-interest income (*Noninterest_Income*) as dependent variables, as these variables indicate distinct business models: the traditional model, which is lending-based, and the non-traditional model, which relies more on fee-based income. This approach allows us to assess whether banks that implement specific technologies decide to transition to a different business model. If such a shift occurs, we would expect a reduction in either variable. The results, presented in **Appendix Tables A2–A3**, indicate that bank digitalization does not appear to drive a fundamental shift in banks' existing business models. We observe that almost all coefficients for individual bank technological solutions are statistically insignificant for interest margins, suggesting that bank technology does not systematically reduce banks' dependence on lending. The only technology with a statistically significant effect is payments, which exhibits a negative coefficient—implying that banks may leverage payment data for credit verification. This finding supports our hypothesis that hardening of information improves the borrowers' screening, and thus reduces bank credit losses.

A similar pattern of statistically insignificant coefficients emerges when analyzing the fee-based banking model, indicating that technology adoption does not significantly alter banks' reliance on fee-based income. Overall, this evidence suggests that banks continue to operate within their established business models even after adopting new technologies, and technology adoption does not appear to drive a structural shift. Therefore, it seems unlikely that bank technology adoption reduces NPLs through a shift of the business model.

Second, it could be the case that banks with specific features may be more predetermined to adopt the technology, and thus shift their business model. To address this concern, we apply PSM to compare digitalized and non-digitalized banks with similar pre-treatment characteristics. We define the digitalized bank sample as institutions that implemented at least five technological solutions (High_Adopters), while the control sample consists of banks with no any technological solutions (Specifications (1)-(3)). Alternatively, we expand the control sample to include, among no-digitalized banks, also low digitalized banks (Specifications (4)-(6)). We estimate propensity scores using a probit model, where the likelihood of bank digitalization is regressed on our bank financial characteristics. We then regress the matched banks on lending volume, interest income, and non-interest income to evaluate the impact of bank digitalization on its operation. To ensure comparability, we perform nearest-neighbor matching with five neighbors (neighbor(5)) and impose a caliper distance of 0.05 to restrict matches to banks with closely aligned characteristics. The results are presented in **Appendix Table A4**. The estimations reveal significant differences between digitalized and non-digitalized banks before matching. However, after matching on observable characteristics, these differences disappear, reinforcing our earlier findings that bank digitalization is not associated with fundamental shifts in operation.

Together, our robustness checks provide strong evidence that technology adoption does not drive a structural transformation in bank revenue composition. Therefore, these results may confirm that the observed reductions in NPLs seem to be driven by enhanced credit risk assessment through more data on borrowers rather than by a strategic reallocation of banking activities.

7.5. Instrumental Variable Regression

7.5.1. Bank-level variation

While our previous analyses test our regression results against selection-bias, the endogeneity concerns may still arise if unobserved factors simultaneously influence both a bank's decision to digitalize and its NPL levels. To further strengthen our causal inference, we employ an instrumental variable (IV) regression, using a Google Trends-based digitalization index (GoogleTrend) as an exogenous proxy for bank digitalization. Google Trends is a service provided by Google that reports a normalized measure of search interest for specific terms over time. The search volume for a term which is in our case the "name of a bank (in any form)", is returned as a relative index, where 100 represents the peak search volume in a given time period, and 0 indicates the lowest level of search interest. We then relate each bank's search volume relative to the most-searched bank in the country, thereby controlling for general internet traffic and broader trends in online banking searches in a country. This ensures that the variation in search intensity reflects differences in bank digitalization rather than broader institutional or social features in a country or internet usage patterns. Google Trends data has been widely used in financial research as a real-time proxy for market sentiment, risk perception, and economic activity (Aslanidis et al., 2022; Choi & Varian, 2012; Vlastakis & Markellos, 2012; see more in Jun et al. (2018)). Prior research in business show that web search data can serve as a proxy for web traffic and online consumer engagement (France et al., 2021) while Kwan et al. (2023) demonstrate that a web traffic is a good measure of bank digitalization (Kwan et al., 2023). We collect Google Trends data at a monthly frequency, averaging it annually for the period 2009–2019. Our IV approach helps mitigate concerns that banks invest in IT only when financially capable or as part of a strategic shift away from traditional lending models. Additionally, our country-year fixed effect interaction allows us to account for sector-wide technological trends, ensuring that our IV strategy isolates the effect of digitalization from broader economic or social fluctuations. **Table 10** presents the regression results.

[Table 10]

The IV regression results reinforce the key findings from the earlier DID regressions. In the first stage, GoogleTrend variable emerges as a strong predictor of bank digitalization, with an estimated coefficient of −0.0072 with a p-value of 0.005. This indicates that higher relative digital search activity is strongly linked to a higher bank digitalization level. In the second stage, greater bank digitalization is found to significantly reduce bank NPLs, as shown by a coefficient of −0.238 which is also highly statically significant. This result suggests that banks that adopt digital technologies seem to benefit from enhanced risk assessment, lowering their credit risk.

Further diagnostic checks confirm the relevance and validity of our instrument. The F-test of excluded instruments ($F = 8.11$, $p = 0.0052$) confirms that GoogleTrend is not weakly correlated with bank digitalization variable. Underidentification test (Anderson LM test: Chi-sq = 8.23, $p = 0.0041$) rejects the null hypothesis that our model is underidentified. Lastly, the Stock-Yogo weak identification test (Cragg-Donald $F = 8.11$) places our instrument between the 15% and 20% maximal IV size critical values. While this F-statistic is below the conventional rule-of-thumb threshold of 10, Stock & Yogo (2005) argue that it remains within an acceptable range for estimation purposes in such models as ours.

7.5.2. Country-level variation

Furthermore, to address potential endogeneity in evaluating the causal impact of Fintech presence on bank digitalization and its subsequent effect on NPLs, we leverage country-level variation as an exogenous source of identification. In our first IV approach, we use the number of Fintech companies within a country (*Fintech_Num*) as an instrument, capturing the competitive pressures Fintech firms impose on banks to accelerate technological development. This instrument provides an exogenous source of variation, as Fintech expansion is driven by broader ecosystem developments rather than banks' internal characteristics.

The second IV approach refines this strategy by interacting the number of Fintech companies with a post-2010 indicator (*Fintech_Num* × *Post2010*), using only Fintech firms established after 2010 as an instrument. This refinement is motivated by the observation that Fintech innovation began gaining significant global traction around 2010, coinciding with advancements in digital technology and increased venture capital investment (Feyen et al., 2021). Moreover, this approach aligns our IV strategy with the treatment period assumed in our DiD regressions, where we posit that banks accelerated technological advancements post-2010. By incorporating temporal variation through this interaction term, we more effectively isolate exogenous changes in Fintech development after 2010, strengthening our identification of the causal effects of digitalization on NPLs.

To further mitigate concerns that our results could be driven by Fintech adoption being disproportionately concentrated in wealthier economies or that the observed decline in NPLs may reflect broader economic performance in Fintech-intensive countries rather than changes in bank lending technology—we incorporate, among bank fixed-effects, the interaction between time- and country fixed effects. This approach ensures that our estimates capture within-bank variation while controlling for macroeconomic trends and country-specific factors that could confound the relationship between digitalization and NPLs. Tables **11–12** present the regression results.

[Table 11]

[Table 12]

The results from both Tables provide interesting results. First, the coefficient of Fintech_Num (**Table 11)** in the first-stage regression is positive and statistically significant, showing that an increase in the number of fintech companies in a country is strongly associated with a rise in banks' adoption of digital solutions (TECH_DEV). This result aligns with our theoretical assumptions stating that fintech competition drives banks to adopt more technological solutions. As discussed, as fintech firms bring innovative products and services to the market, they have exerted competitive pressure on traditional banks, motivating banks to spur the technological development and meet evolving customer expectations (Valver & Fernandez, 2020; Zachariadis & Ozcan, 2022; Zhao et al., 2022). In the second stage, the coefficient on Tech_Dev is negative and statistically significant, indicating that higher levels of bank technological development, prompted by fintech competition, are associated with a reduction in the bank NPLs. This negative relationship suggests that as banks increase their digital capabilities, they enhance their credit risk management. These findings support our hypothesis that fintech-driven digitalization can have stability-enhancing effects on banks, not just through direct operational improvements but also through the access to alternative data which improve the credit scoring assessment, and reduce banks NPLs.

Similar results we notice from **Table 12.** The results obtained with Fintech_Num*Post2010 are consistent with our theoretical framework and previous results, suggesting that fintech growth intensifies technological adoption in banks, enhancing their credit risk management assessment. The results from first-stage regression shows that an instrument yields a coefficient of 0.002, indicating a positive and statistically significant relationship between post-2010 fintech growth and banks' adoption of digital solutions. This result additionally supports our theory that the post-2010 competitive environment intensified the influence of fintech on bank digital transformation. At the same time, the results from the second-stage regression indicate that higher levels of bank digitalization, induced by fintech competition, are associated with a reduction in NPL share.

The validity of our instruments is assessed using multiple diagnostic tests presented in in the Table. The F-test of excluded instruments allows us to reject the hypothesis that fintech variable is weakly correlated with bank digitalization. The underidentification test (Anderson LM) produces a value of 36.21 with a p-value of 0.000, strongly rejecting the null hypothesis of underidentification and confirming that the instruments are relevant and correlated with the endogenous variables. Furthermore, the weak identification test (Cragg-Donald Wald F-Statistic) yields a value of 38.52, significantly exceeding the critical value of 16.38 for a 10% maximal IV size, indicating that the instruments are sufficiently strong. Moreover, the Sargan test indicates that the model is exactly identified, meaning there are no overidentifying restrictions to test (Sargan, 1958). While this does not directly test for the validity of the instrument, the exactly identified nature of the model ensures that the model cannot suffer from overidentification problems.

8. Robustness for Systemic Risk

Although our technological development data is unique, its collection was time-consuming, limiting our analysis. To test the robustness of our results, we extend our sample to include banks from all developed countries for which the systemic risk measure (SRISK) was available. This would allow us to extend our analysis to a relatively homogeneous group of banks for testing the impact of technological development on systemic risk. This expansion increases the number of observations to 2453 over the same time frame (2008-2019) and covers both smaller and larger banks. Similarly, as in the previous analysis, we use the INTANGIBLE_ASSET as an alternative technological development to our TECH_DEV. We present our regression results in **Table 13.** We provide the regression results using a wider set of systemic risk measures, including:

- LRMES (LRMES), or Long-Run Marginal Expected Shortfall, is the expected fractional loss of the bank equity when the MSCI World Index declines significantly in a six-month period. It is calculated as 1-exp(log(1-d)*beta), where d is the six-month crisis threshold for the market index decline and its default value is 40%;
- Beta is the Beta of the firm with respect to the MSCI World Index, using Rob Engle's Dynamic Conditional Beta model;
- Correlation (CORR) is the dynamic conditional correlation between the equity return on a stock and the return on the MSCI All-Country World Index;
- Volatility (VOL) is the annualized volatility of the equity of the company. It is estimated with a GJR-GARCH model that is updated daily;

- Leverage (LEV) is the Quasi Leverage of a company which is 1 plus its book value of liabilities divided by its market value of equity.

[Table 13]

The regression results prove our baseline conclusions documenting a negative relationship between bank technological development and systemic risk. Specifically, the estimations document that more technologically advanced banks, i.e. banks with relatively higher intangible assets, can reduce systemic risk in the banking sector, likely due to less correlated decisions enhancing the diversification in the system. Banks that invest in new technologies are also less sensitive to market volatility (Specification (5)) and general market conditions (Specification (4)). Additionally, they have a higher ability to absorb losses during times of market stress (Specification (3)). All of these results support our previous conclusions that digitalization generally leads to a decrease in systemic risk.

9. Conclusion

The technological development has undoubtedly brought numerous benefits in the banking sector, but it is crucial to consider the potential risks and downsides associated with banks' transformation. These risks relate to the impact of "hardening" of information and potential effects on bank credit risk as well as interconnection between banks. Global organizations like the Bank for International Settlements or the Financial Stability Board have raised concerns about the increased risk that may arise from the ongoing digitalization process related to the interconnection of banks in their decisions due to shared data, decision patterns or correlation in the technology providers (BIS, 2020; BIS, 2019; FSB, 2019).

To address these concerns and contribute to the understanding of the impact of technological development in the banking sector, our study focuses on analyzing the technological development of 63 major European and US banks over a period of 11 years, from 2009 to 2019. We collected the information about the specific technological solutions implemented by these banks, their type, source of adoption, and the interlinkages between different technology-providers. We extend this analysis to 363 other banks for which we use intangible asset as a measure of level of technological development. This alternative way of sample selection and alternative digitalization measure provide also an important robustness check for our baseline analyses. Using both sample we aim to examine the effects of bank technological development on their NPLs and systemic risk measures, providing into insight into the role of technology on bank credit risk and financial stability.

In our study we employ various econometric techniques to ensure we minimize the potential endogeneity concerns, starting from static and dynamic DID TWFE models, synchronicity analysis, and ending up with 2SLS IV.

The findings of our study are robust across different methodologies and reveal several important conclusions. Firstly, we observe that banks with a higher degree of technological development tend to exhibit lower levels of NPLs. We relate this result to a wide array of financial and behavioral data, more digitalized banks have access to thanks to their technology. Moreover, we find that this effect becomes more pronounced as digitalization progresses over time and as banks adopt a greater number of technological solutions. Our findings indicate that more technologically advanced banks can reduce on average 1.9 percentage point in their NPLs thanks to the access to different data, which improves their informational efficiency, and consequently their credit risk.

Additionally, we find that bank technological development has a mitigating impact on systemic risk, with electronic payment solutions demonstrating the most significant influence in risk reduction. Based on our estimations, the adoption of one additional technological solution by banks can lead to a decline in systemic risk by 0.18 percentage points, potentially saving the banking sector up to $3 billion in distress-related costs. This result might suggest banks use the technology to attract specific clients or segments which may enhance individual specialization, but system-wide diversification in the banking sector. This result is further supported by the synchronicity analysis where we see that banks risk measures correlate less across more digitalized banks.

Interestingly, our analysis also reveals that the source of technology adoption plays a crucial role in shaping the effects on systemic risk. Specifically, when banks purchase technology solutions, we observe a decreasing effect on systemic risk measures. This outcome can be attributed to the advantages of a "tailored" design approach, which allows banks to select solutions that align closely with their specific needs and risk culture.

However, we find that the concentration of technology providers to banks increases the systemic risk. This finding raises concerns about the potential risks associated with relying heavily on a limited number of technology providers within the banking sector. More specifically, we argue that the concentration of technology providers seems to increase risk, probably through more correlated decision patterns utilized by the same providers.

The findings of our research have significant implications for policymaking. First, they may provide a plausible explanation for the recent financial instability in the US banking sector regarding the Silicon Valley Bank, suggesting that digitalized banks are more prone to bank runs due to their more concentrated client base. On the other hand, their specialized nature may offer more diversification in the system limiting the risk of systemic crises. Second, our analysis also uncovers a potential increase in sector-wide risk. Specifically, the regression results suggest that partnerships between banks and fintech companies could pose material risks when identical technology solutions are implemented across multiple institutions. Consequently, the regulators should counteract the concentration of technology providers to the banking sector and monitor the nature of technologies provided to different institutions by external providers.

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Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
BANK VARIBLES					
Credit_Activity	650	51.496	17.322	2.555	80.638
Noninterest_Income	657	43.762	19.963	-85.976	155.693
Efficiency	657	63.937	20.025	-48.163	288.31
ROA	658	0.389	1.043	-11.546	3.965
TIER1_Capital	626	13.551	3.486	4.3	29.36
NPL_Ratio	639	0.037	0.06	0	0.495
InterestMargin	657	54.196	17.862	1.651	92.025
Size	658	19.447	1.539	15.577	21.646
SRISK	639	25,736.79	34,205.72	-30,274.1	136,743
SRISK (%)	639	2.352	3.158	0	14.44
DIGITALIZATION VARIABLES					
Automation	486	0.342	0.475	0	1
Blockchain	549	0.313	0.464	0	1
Robo_Adv	392	0.393	0.489	0	1
Analytics	464	0.379	0.486	0	1
Online_Lending	393	0.328	0.47	0	1
Electronic_Payment	639	0.67	.471	0	1
Personal_Fin	396	0.419	0.494	0	1
Reg_Tech	441	0.408	0.492	0	1
Tech_Dev	756	1.048	2.061	0	8
Investment	756	0.421	0.494	0	1
Outsourcing	756	0.060	0.237	0	1
In-House	756	0.153	0.361	0	1
Tech_Sharing	756	2.400	6.688	0	44
Intangible_Asset	620	0.279	0.281	0	2.418
Fintech_Num	756	21.3	72.153	0	784
GoogleTrend	233	47.978	26.834	0	93.333
COUNTRY VARIABLES					
Inflation	756	1.539	1.516	-4.478	15.402
GDP_Growth	756	1.266	3.031	-14.434	25.176
Concentration	630	64.085	17.247	34.317	98.867

Table 2: Static DID - The impact of bank technological development on NPLs

The Table present the regression results using the static DID for a treated group of banks having adopted more than four digital solutions after 2010; zero for all other banks. The treatment period starts in 2011. Interaction is defined as a High_Adopters*Treatment_Years where the Treatment_Years account for treatment period between 2011 and 2019. Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * p < 0.1, ** p < 0.05, *** p < 0.01

VARIABLES	(1) **NPL_Ratio**	(2) **NPL_Ratio**	(3) **NPL_Ratio**	(4) **NPL_Ratio**
High_Adopters	0.00532	0.00873	0.00359	0.0122
	(0.00506)	(0.00540)	(0.00577)	(0.00765)
Treatment_Years	0.0200**	0.0163*	0.00408	-0.00428
	(0.00847)	(0.00924)	(0.0107)	(0.0135)
High_Adopters*Treatment_Years	-0.0197**	-0.0180*	-0.0189**	-0.0193**
	(0.00861)	(0.00906)	(0.00754)	(0.00726)
L1.Size				-0.0217**
				(0.00997)
L1.ROA				-0.00693***
				(0.00257)
L1.Efficiency				9.26e-05
				(6.68e-05)
L1.Credit_Activity				-0.000573
				(0.000522)
L1.Tier1_Capital				0.00199
				(0.00168)
GDP_Growth			0.00139	0.00230
			(0.000970)	(0.00158)
Inflation			-0.00752	-0.00514
			(0.00567)	(0.00569)
Concentration			0.00145*	0.00117
			(0.000851)	(0.000718)
Constant	0.0235***	0.0132*	-0.0547	0.388**
	(0.00599)	(0.00681)	(0.0486)	(0.185)
Observations	639	639	528	445
R-squared	0.058	0.098	0.202	0.229
Bank Controls				YES
Macro Controls			YES	YES
Bank FE		YES	YES	YES
Time FE	YES	YES	YES	YES

Table 3: Dynamic DID - The impact of bank technological development on NPLs

The Table present the regression results using the dynamic DID for a treated group of banks having adopted more than four digital solutions after 2010; zero for all other banks. Interaction is defined as a High_Adopters*

Year_Dummy which is equaled to one for a given year and zero for others. Bank control variables include: Size, Efficiency, ROA, Credit_Activity, TIER1 while country controls include: GDP_Growth, Inflation and Concentration. Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	NPL_Ratio	**NPL_Ratio**	**NPL_Ratio**	**NPL_Ratio**
Year_Dummy2009* High_Adopters	-0.00557**	-0.00560**	0.000180	-0.009
	(0.00225)	(0.00225)	(0.0104)	(0.009)
Year _Dummy2010* High_Adopters	-0.0080	-0.0082	-0.0026	-0.0145
	(0.0053)	(0.0052)	(0.0108)	(0.0051)
Year_Dummy2011* High_Adopters	-0.0187**	-0.0187**	-0.0236**	-0.0236**
	(0.00737)	(0.00740)	(0.00935)	(0.00960)
Year_Dummy2012* High_Adopters	-0.0292***	-0.0291***	-0.0370***	-0.0338***
	(0.0100)	(0.0100)	(0.0104)	(0.0113)
Year_Dummy2013* High_Adopters	-0.0348***	-0.0348***	-0.0335***	-0.0234*
	(0.0129)	(0.0129)	(0.0110)	(0.0138)
Year_Dummy2014* High_Adopters	-0.0366***	-0.0363***	-0.0334***	-0.0279**
	(0.0132)	(0.0132)	(0.00945)	(0.0125)
Year_Dummy2015* High_Adopters	-0.0337**	-0.0333**	-0.0357***	-0.0271***
	(0.0147)	(0.0148)	(0.0102)	(0.00950)
Year_Dummy2016* High_Adopters	-0.0302*	-0.0302*	-0.0306***	-0.0264**
	(0.0157)	(0.0158)	(0.0105)	(0.0116)
Year_Dummy2017* High_Adopters	-0.0266*	-0.0263	-0.0339**	-0.0350**
	(0.0156)	(0.0157)	(0.0153)	(0.0157)
Year_Dummy2019* High_Adopters	-0.0143	-0.0141	-0.0574**	-0.0640**
	(0.0110)	(0.0111)	(0.0281)	(0.0299)
Observations	537	537	436	417
R-squared		0.112	0.253	0.378
Bank controls				YES
Macro controls			YES	YES
Bank FE		YES	YES	YES
Time FE	YES	YES	YES	YES

Table 4: Staggered DID - The impact of bank technological development on NPLs

The Table presents the regression results using the staggered DID for a treated group of banks having adopted more than four digital solutions (High_Adopters) in a given year; zero for all other banks. Interaction is defined as High_Adopters*Treatment_Years where the Treatment_Years account for years since bank adoption of a first technological solution. The regression results include bank controls (not reported in the Table) such as: Size, Efficiency, ROA, Credit_Activity, TIER1 and country controls include GDP_Growth, Inflation and Concentration. Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * p < 0.1, ** p < 0.05, *** p < 0.01.

	(1) **NPL_Ratio**	(2) **NPL_Ratio**	(3) **NPL_Ratio**	(4) **NPL_Ratio**
High_Adopters*Treatment_Years	-0.0239**	-0.0223**	-0.0232**	-0.0199***
	(0.0107)	(0.0110)	(0.00907)	(0.00615)
Observations	537	537	436	417
R-squared	0.067	0.108	0.221	0.374
Bank controls				YES
Macro controls			YES	YES
Bank FE		YES	YES	YES
Time FE	YES	YES	YES	YES

Table 5: The impact of bank technological development on systemic risk

The Table presents the linear regression of digitalization on the systemic risk measures. SRISK expressed in mln USD is a widely accepted indicator of systemic risk measuring the expected fractional loss of equity when the MSCI All-Country World Index falls by the crisis threshold (40%) within a six-month period. The prudential capital requirement *k* is set to be 8% for all banks in the sample. Positive values for SRISK imply capital shortfall whereas negative values are associated with a capital surplus (no distress). SRISK% measures the proportional contribution of each bank's SRISK to the total positive SRISK of the financial system (SRISK%) (Brownlees and Engle,2012). TECH_DEV is an index capturing the number of bank technological solutions each year. Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * p < 0.1, ** p < 0.05, *** p < 0.01

	SRISK%	**SRISK**
Tech_Dev	-0.185**	-3.0e+03***
	(0.074)	(687.146)
L1.Size	0.725**	2.5e+04***
	(0.330)	(3063.665)
L1. TIER1_Capital	-0.136**	-1.5e+03**
	(0.064)	(593.073)
L1.Credit_Activity	-0.013	66.270
	(0.012)	(111.293)
L1.Noninterest_Income	-0.005	-53.520
	(0.007)	(62.074)
L1.Liquidity	0.004	17.070
	(0.006)	(53.517)
L1.NPL_Ratio	0.008	639.514***
	(0.025)	(229.486)
L1. ROA	-0.140	-492.933
	(0.165)	(1531.313)
GDP_Growth	0.008	597.517
	(0.045)	(414.323)
Inflation	-0.046	-1.3e+03
	(0.087)	(807.036)
Observations	491	491
R-squared	0.874	0.900
Bank FE	YES	YES
Time FE	YES	YES

Table 6: The impact of the type of bank adopted solutions on SRISK

The Table presents the linear regression of digitalization on the systemic risk measure - SRISK. SRISK expressed in mln USD is a widely accepted indicator of systemic risk measuring the expected fractional loss of equity when the MSCI All-Country World Index falls by the crisis threshold (40%) within a six-month period. The prudential capital requirement *k* is set to be 8% for all banks in the sample. Positive values for SRISK imply capital shortfall whereas negative values are associated with a capital surplus (no distress). TECH_DEV is an index capturing the number of bank technological solutions in a given year. Regression controls for the type of solutions adopted by banks as: Automation, Blockchain, Robo_Adv, Analtytics, Online_Lending, Electronic_Payment, Personal_Fin, Reg_Tech. The variables are defined as a binary variable indicating whether a specific solution has been adopted by a bank in a given year (a dummy equaling one and zero if not). The regressions also control for the general level of bank technological development. Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

VARIABLES	(1) SRISK	(2) SRISK	(3) SRISK	(4) SRISK	(5) SRISK	(6) SRISK	(7) SRISK	(8) SRISK
L1.Tech_Dev	0.559*	0.539*	0.707**	0.612*	0.534	0.786**	0.550*	0.517
	(0.326)	(0.322)	(0.328)	(0.324)	(0.328)	(0.331)	(0.326)	(0.325)
L1.Size	-0.132**	-0.126**	-0.129**	-0.143**	-0.135**	-0.139**	-0.131**	-0.141**
	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.065)	(0.064)
L1. TIER_ Capital	-0.015	-0.015	-0.011	-0.017	-0.017	-0.017	-0.016	-0.019
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
L1.Credit_Activity	-0.005	-0.006	-0.006	-0.005	-0.005	-0.002	-0.005	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
L1.Noninterest_Income	0.007	0.006	0.004	0.007	0.007	0.006	0.007	0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
L1.Liquidity	0.013	0.007	0.012	0.009	0.012	0.011	0.012	0.017
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
L1.NPL_Ratio	-0.097	-0.150	-0.116	-0.111	-0.085	-0.093	-0.095	-0.063
	(0.165)	(0.164)	(0.164)	(0.164)	(0.166)	(0.163)	(0.165)	(0.165)
L1. ROA	0.011	-0.004	0.015	0.006	0.008	0.010	0.009	0.005
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.044)	(0.045)	(0.045)
GDP_Growth	-0.049	-0.052	-0.025	-0.053	-0.053	-0.054	-0.049	-0.057
	(0.088)	(0.087)	(0.087)	(0.087)	(0.088)	(0.087)	(0.088)	(0.087)
Automation	0.097							
	(0.286)							
Blockchain		-0.613***						
		(0.208)						
Robo_Adv			-0.669**					
			(0.263)					
Analytics				-0.507**				
				(0.224)				
Online_Lending					0.231			
					(0.329)			
Electronic_Payment						-0.744***		
						(0.251)		
Personal_Fin							0.143	
							(0.333)	
Reg_Tech								0.457*
								(0.255)
Observations	491	491	491	491	491	491	491	491
R-squared	0.872	0.875	0.874	0.874	0.873	0.875	0.872	0.873
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 7: The impact of the source of a bank adopted solution on SRISK

The Table presents the linear regression of digitalization on the systemic risk measures. SRISK is a widely accepted indicator of systemic risk measuring the expected fractional loss of equity when the MSCI All-Country World Index falls by the crisis threshold (40%) within a six-month period. The prudential capital requirement *k* is set to be 8% for all banks in the sample. Positive values for SRISK imply capital shortfall whereas negative values are associated with a capital surplus (no distress) expressed in USD. SRISK% measures the proportional contribution of each bank's SRISK to the total positive SRISK of the financial system (SRISK%) (Brownlees and Engle,2012). Tech_Dev is an index capturing the number of bank technological solutions in a given year. Investment*Tech_Dev, In-House*Dev_Tech and Outsourcing*Tech_Dev are interaction terms indicating whether any technological solution has been adopted by a bank using this form; if not then zero.
Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	SRISK%	SRISK%	SRISK%	SRISK	SRISK	SRISK
Tech_Dev	0.122	-0.205***	-0.191**	448.231	-2.8e+03***	-3.0e+03***
	(0.101)	(0.076)	(0.077)	(929.463)	(704.275)	(719.654)
Investment* Tech_Dev	-0.068***			-747.815***		
	(0.015)			(142.537)		
In-House* Dev_Tech		0.043			-322.143	
		(0.036)			(339.087)	
Outsourcing* Tech_Dev			0.028			259.239
			(0.110)			(1019.090)
L1.Size	0.766**	0.722**	0.722**	2.6e+04***	2.5e+04***	2.5e+04***
	(0.323)	(0.330)	(0.330)	(2972.755)	(3064.098)	(3069.697)
L1. Equity Ratio	-0.105*	-0.130**	-0.137**	-1.1e+03*	-1.5e+03**	-1.5e+03**
	(0.063)	(0.064)	(0.064)	(578.916)	(595.275)	(594.955)
L1.Loan Activity	-0.014	-0.012	-0.013	49.515	62.817	67.726
	(0.012)	(0.012)	(0.012)	(107.992)	(111.365)	(111.564)
L1.Noninterest_Income	-0.006	-0.005	-0.005	-69.486	-54.067	-53.549
	(0.007)	(0.007)	(0.007)	(60.283)	(62.084)	(62.143)
L1.Liqudity	0.004	0.004	0.004	21.264	20.047	15.665
	(0.006)	(0.006)	(0.006)	(51.913)	(53.615)	(53.861)
L1.NPL_Ratio	0.008	0.010	0.009	632.853***	628.512***	643.515***
	(0.024)	(0.025)	(0.025)	(222.585)	(229.805)	(230.280)
L1.ROA	-0.138	-0.137	-0.136	-468.131	-514.475	-459.633
	(0.161)	(0.165)	(0.166)	(1485.246)	(1531.658)	(1538.596)
GDP_Growth	0.007	0.007	0.007	594.694	605.784	593.889
	(0.044)	(0.045)	(0.045)	(401.857)	(414.462)	(415.029)
Inflation	0.006	-0.038	-0.045	-744.129	-1.4e+03*	-1.3e+03
	(0.086)	(0.087)	(0.087)	(790.422)	(809.824)	(809.961)
Observations	491	491	491	491	491	491
R-squared	0.897	0.892	0.892	0.919	0.914	0.914
Bank FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Table 8: The impact of the source of a bank adopted solution on SRISK

The Table presents the linear regression of digitalization on the systemic risk measures using the bank-and macro control, bank-and time fixed effects. SRISK is a widely accepted indicator of systemic risk measuring the expected fractional loss of equity when the MSCI All-Country World Index falls by the crisis threshold (40%) within a six-month period. The prudential capital requirement *k* is set to be 8% for all banks in the sample. Positive values for SRISK imply capital shortfall whereas negative values are associated with a capital surplus (no distress) expressed in USD. SRISK% measures the proportional contribution of each bank's SRISK to the total positive SRISK of the financial system (SRISK%) (Brownlees and Engle,2012). TECH_DEV is an index capturing the number of bank technological solutions adopted by a bank in a given year. TECH_SHARING is the number of banks sharing the same technology provider with a bank *i* at time *t.* The regression results include bank controls (not reported in the Table) such as: Size, Efficiency, ROA, Credit_Activity, Noninterest_Income, Liquidity, TIER1 and country controls include GDP_Growth, Inflation and Concentration.Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	SRISK%	**SRISK%**	**SRISK**	**SRISK**
	(1)	**(2)**	**(3)**	**(4)**
Tech_Dev	-0.111	-0.108**	-2.2e+03***	-392.676
	(0.075)	(0.054)	(698.178)	(505.509)
Tech_Sharing	0.002		46.121***	
	(0.002)		(17.539)	
Observations	491	491	491	491
R-squared	0.891	0.892	0.912	0.911
Bank controls	YES	YES	YES	YES
Macro controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Table 9: Robustness - The impact of bank technological development on NPLs using an alternative measure of bank technological development

The Table presents the regression results using the dynamic DID for a treated group of banks being at a seventy-fourth quantile of bank technological development distribution using the Intangible_Asset. Interaction is defined as a High_Intangible_Asset *Treatment_Year where the Treatment_Year is a dummy equal to one for the periods between 2011 and 2019. Standard errors are clustered at the bank level. Additionally, the model estimates the interaction between the treated banks and individual years to capture the heterogeneity in the bank technological effects across time. The regression results include bank controls (not reported in the Table) such as: Size, Efficiency, ROA, Credit_Activity, TIER1 and country controls include GDP_Growth, Inflation and Concentration.Standard errors are in parentheses indicating * p < 0.1, ** p < 0.05, *** p < 0.01

VARIABLES	(1) NPL_ Ratio	(2) NPL_ Ratio	(3) NPL_ Ratio	(4) NPL_ Ratio
Treatment_Year2009*High_Intangible_Asset	-0.00169	-0.00196	0.000843	-0.00363
	(0.00340)	(0.00345)	(0.00376)	(0.00641)
Treatment_Year2010* High_Intangible_Asset	-0.00718	-0.00712	-0.00415	-0.00732
	(0.00507)	(0.00512)	(0.00535)	(0.00618)
Treatment_Year2011* High_Intangible_Asset	-0.0201***	-0.0203**	-0.0176**	-0.0152**
	(0.00774)	(0.00780)	(0.00830)	(0.00669)
Treatment_Year2012* High_Intangible_Asset	-0.0297***	-0.0302***	-0.0287***	-0.0307***
	(0.00911)	(0.00916)	(0.00882)	(0.0111)
Treatment_Year2013* High_Intangible_Asset	-0.0324***	-0.0327**	-0.0302**	-0.0172**
	(0.0125)	(0.0125)	(0.0125)	(0.00754)
Treatment_Year2014* High_Intangible_Asset	-0.0288***	-0.0293***	-0.0268**	-0.0161**
	(0.0105)	(0.0106)	(0.0101)	(0.00716)
Treatment_Year2015* High_Intangible_Asset	-0.0253**	-0.0258**	-0.0238**	-0.0134*
	(0.0107)	(0.0108)	(0.0102)	(0.00680)
Treatment_Year2016* High_Intangible_Asset	-0.0251**	-0.0256**	-0.0257**	-0.0186**
	(0.0109)	(0.0109)	(0.0111)	(0.00825)
Treatment_Year2017* High_Intangible_Asset	-0.0194***	-0.0204***	-0.0171***	-0.0161**
	(0.00621)	(0.00657)	(0.00638)	(0.00708)
Treatment_Year2019* High_Intangible_Asset	-0.0205***	-0.0214***	-0.0363***	-0.0457***
	(0.00735)	(0.00769)	(0.0117)	(0.0139)
Observations	604	604	501	476
R-squared	0.04	0.167	0.213	0.464
Bank controls				YES
Macro controls			YES	YES
Bank FE	YES	YES	YES	YES
Time FE		YES	YES	YES

Table 10: Robustness - The effect of GoogleTrend on bank NPLs using 2SLS IV regression.

The Table presents the results of the first-and second-stage regressions of the IV regressions with bank-and time-fixed effects of bank technological development on NPLs (Specifications (1)-(2)). Specifications (3)-(4) additionally include the interaction between country-time fixed-effects. We instrumentalize bank technological development (Tech_Dev) with a Google Trends (GooleTrend) variable measuring the search volume of a bank name per month, averaging these data per year. The index ranges from 0 to 100 and is scaled to the index of a mostly searched bank in a country to capture the institutional and social features of a bank operation. Robust standard errors are shown in parentheses. First-stage and second-stage refer to the 2SLS IV regression results for the first-and second stage estimations, respectively. The regression results include bank controls (not reported in the Table) such as: Size, Efficiency, ROA, Credit_Activity, TIER1 and country controls include GDP_Growth, Inflation and Concentration. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	First-Stage Regression	**Second-Stage Regression**	**First-Stage Regression**	**Second-Stage Regression**
VARIABLES	**(1) Tech_Dev**	**(2) NPL_Ratio**	**(3) Tech_Dev**	**(4) NPL_Ratio**
GoogleTrend	-0.007***		-0.007***	
	(0.003)		(0.002)	
L1.Tech_Dev		-0.229**		-0.238***
		(0.096)		(0.094)
Observations	148	148	148	148
R-squared		0.147		0.097
Bank FE	YES	YES	YES	YES
Time FE	YES	YES		
Country*Time FE			YES	YES
Underidentification test				
Anderson canon. corr. LM	7.51	7.507	8.23	8.233
statistic (p-value)	(0.006)	(0.006)	(0.004)	(0.004)
Weak identification test				
Cragg-Donald Wald F-statistic	6.85	6.853	8.11	8.111
10% maximal IV size	(16.38)	(16.38)	(16.38)	(16.38)
20% maximal IV size	(6.66)	(6.66)	(6.66)	(6.66)
Sargan statistic		exactly identified		exactly identified
F-test of excluded instruments (p-value)	6.85 (0.010)			

Table 11: Robustness - The effect of fintech development on bank NPLs using 2SLS IV regression.

The Table presents the results of the first-and second-stage regressions of the IV regressions with bank-and time-fixed effects of bank technological development on NPLs (Specifications (1)-(2)). Specifications (3)-(4) additionally include the interaction of country-time fixed-effects. We instrumentalize bank technological development (Tech_Dev) with a number of fintech companies in a country of a bank headquarter (Fintech_Num). Robust standard errors are shown in parentheses. First-stage and second-stage refer to the 2SLS IV regression results for the first-and second stage estimations, respectively. The regression results include bank controls (not reported in the Table) such as: Size, Efficiency, ROA, Credit_Activity, TIER1 and country controls include GDP_Growth, Inflation and Concentration. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	First-Stage Regression	**Second-Stage Regression**	**First-Stage Regression**	**Second-Stage Regression**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
	Tech_Dev	**NPL_Ratio**	**Tech_Dev**	**NPL_Ratio**
Fintech_Num	0.002***		0.003***	
	0.000		(0.000)	
L1.Tech_Dev		-0.021**		-0.023**
		(0.011)		(0.011)
Observations	392	392	392	392
R-squared		0.147		0.097
Bank FE	YES	YES	YES	YES
Time FE	YES	YES		
Country*Time FE			YES	YES
Underidentification test				
Anderson canon. corr. LM statistic (p-value)	34.764 (0.000)	34.764 (0.000)	33.70 (0.000)	33.698 (0.000)
Weak identification test				
Cragg-Donald Wald F-statistic	36.81	36.807	36.331	36.331
10% maximal IV size	(16.38)	(16.38)	(16.38)	(16.38)
Sargan statistic		exactly identified		exactly identified
F-test of excluded instruments (p-value)	36.81 (0.000)		36.33 (0.000)	

Table 12: Robustness - The effect of fintech development on bank NPLs using the 2SLS IV regression.

The Table presents the results of the first-and second-stage regressions of the IV regressions with bank-and time-fixed effects of bank technological development on NPLs (Specifications (1)-(2)). Specifications (3)-(4) additionally include the interaction of country-time fixed-effects. We instrumentalize bank technological development (Tech_Dev) with a number of fintech companies after 2010 in a country of bank headquarter (Fintech_Num*Post2010). Robust standard errors are shown in parentheses. First-stage and Second-stage refer to the 2SLS IV regression results for the first-and second stage estimations, respectively. The regression results include bank controls (not reported in the Table) such as: Size, Efficiency, ROA, Credit_Activity, TIER1 and country controls include GDP_Growth, Inflation and Concentration *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	First-Stage Regression	**Second-Stage Regression**	**First-Stage Regression**	**Second-Stage Regression**
VARIABLES	**(1) Tech_Dev**	**(2) NPL_Ratio**	**(1) Tech_Dev**	**(2) NPL_Ratio**
Fintech_Num*Post2010	0 .002***		0.002***	
	(0.000)		(0.000)	
L1.Tech_Dev		-0.021**		-0.023**
		(0.011)		(0.011)
Observations	392	392	392	392
R-squared		0.147		
Bank FE	YES	YES	YES	YES
Time FE	YES	YES		
Country*Time FE			YES	YES
Underidentification test				
Anderson canon. corr. LM statistic (p-value)	36.21 (0.000)	36.212 (0.000)	33.70 (0.000)	33.698 (0.000)
Weak identification test				
Cragg-Donald Wald F-statistic	38.52	38.525	36.33	36.331
10% maximal IV size	(16.38)	(16.38)	(16.38)	(16.38)
Sargan statistic		exactly identified		exactly identified
F-test of excluded instruments (p-value)	36.81 (0.000)		36.33 (0.000)	

Table 13: Robustness Check - The impact of intangible asset ratio on systemic risk measures

The Table presents the linear regression of technological development on the systemic risk measures using the extended bank sample. SRISK is a widely accepted indicator of systemic risk measuring the expected fractional loss of equity when the MSCI All-Country World Index falls by the crisis threshold (40%) in a six-month period. The prudential capital requirement k is set to be 8% for all firms in the sample. Positive values for SRISK implies capital shortfall whereas negative values are associated with a capital surplus (no distress). SRISK is expressed in absolute values as USD capital shortfall as well as in relative terms. In case of the latter, the proportional contribution of each bank's SRISK to the total positive SRISK of the financial system (SRISK%) is estimated (Brownlees and Engle,2012). Other measures are components of SIRISK as: *lrmes* indicates the Long-Run Marginal Expected Shortfall; *Beta* and *CORR* indicate the co-movement bank returns with market returns; *VOL* indicates the market volatility while *LEV* is a leverage measure. INTANGIBLE_ASSET measures bank's technological development and is defined as a value of bank's intangible asset excluding goodwill to total bank assets for a given year. Standard errors in parentheses indicating * p < 0.1, ** p < 0.05, *** p < 0.01

	(1) **SRISK%**	(2) **SRISK**	(3) **lRMES**	(4) **BETA**	(5) **CORR.**	(6) **VOL.**	(7) **LEV.**
Intangible_Asset	-0.073***	-478.648***	-0.612***	-0.021***	0.002	-0.649*	-0.084
	(0.023)	(176.932)	(0.213)	(0.007)	(0.002)	(0.372)	(0.235)
L1.Size	-0.003	34.881	0.771*	0.021	0.019***	-1.768**	0.308
	(0.049)	(372.941)	(0.448)	(0.014)	(0.005)	(0.783)	(0.495)
L1. Liquidity	0.000	8.720	-0.005	-0.000	-0.000*	-0.022*	-0.031***
	(0.001)	(6.045)	(0.007)	(0.000)	(0.000)	(0.013)	(0.008)
L1.ROA	-0.068**	-771.757***	-0.466*	-0.019**	0.013***	-1.420***	-1.310***
	(0.027)	(203.058)	(0.244)	(0.008)	(0.003)	(0.427)	(0.269)
L1.TIER1_Capital	0.005	-26.386	0.237**	0.009***	-0.002	0.026	-0.251**
	(0.010)	(78.193)	(0.094)	(0.003)	(0.001)	(0.164)	(0.104)
L1.Noninterest_Income	0.002*	27.057***	-0.007	-0.000	-0.000**	0.030*	0.039***
	(0.001)	(7.831)	(0.009)	(0.000)	(0.000)	(0.016)	(0.010)
L1.NPL_Ratio	0.010	80.790	-0.105	-0.004*	-0.003***	0.388***	0.299***
	(0.007)	(55.444)	(0.067)	(0.002)	(0.001)	(0.116)	(0.074)
GDP_Growth	-0.025**	-130.517*	-0.159*	-0.006*	-0.002*	-0.008	-0.137
	(0.010)	(78.376)	(0.094)	(0.003)	(0.001)	(0.165)	(0.104)
Inflation	-0.003	71.114	0.154	0.003	0.001	-0.169	0.236**
	(0.010)	(79.531)	(0.096)	(0.003)	(0.001)	(0.167)	(0.106)
Observations	2073	2073	2073	2073	2073	2073	2073
Number of banks	238	238	238	238	238	238	238
R-squared	0.766	0.842	0.785	0.761	0.870	0.607	0.729
Bank FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES

Appendix

Table A1: Variable definitions

Variable	Definition
A. Bank-level variables	
Size	Natural logarithm of assets (in millions) in constant prices
Credit_Activity	Ratio of net loans to total assets
Tier1_Capital	Tier1 capital to risk-weighted asset
Noninterest _Income	Non-interest income to bank operating income
Interest_Income	Interest income to operating income
NPL_Ratio	Ratio of non-performing loans to total bank loans
ROA	Net income to bank averaged asset
Liquidity	Ratio of deposit to loans
Efficiency	Ratio of costs to bank overheads
Intangible_Asset	Ratio of a value of bank intangible asset to total asset at time *t*
SRISK	SRISK expressed in mln USD is a widely accepted indicator of systemic risk measuring the expected fractional loss of equity when the MSCI All-Country World Index falls by the crisis threshold (40%) within a six-month period. The prudential capital requirement *k* is set to be 8% for all banks in the sample. Positive values for SRISK imply capital shortfall whereas negative values are associated with a capital surplus (no distress).
Srisk (%)	The proportional contribution of each bank's SRISK to the total positive SRISK of the financial system (SRISK%).
	The Long-Run Marginal Expected Shortfall.
LRMES	The co-movement bank returns with market returns.
Beta	The co-movement bank returns with market returns.
Corr	Stock volatility.
Vol	A bank's leverage.
LEV	
B. Digitalization variables	
Automation	Binary variable equaling one if a bank adopted Automation software for data processing; zero otherwise.
Blockchain	Binary variable equaling one if a bank has access to a Blockchain platform; zero otherwise.
Analytics	Binary variable equaling one if a bank has adopted a data analytical platform for processing and analyzing the big data; zero otherwise.
Online_Lending	Binary variable equaling one if a bank has adopted an online lending platform; zero otherwise.
Electronic_Payment	Binary variable equaling one if a bank has adopted any electronic payment system; zero otherwise.
Personal_Fin	Binary variable equaling one if a bank has adopted a platform offering its customers various financial products; zero otherwise.
Reg_Tech	Binary variable equaling one if a bank has adopted a regulatory technology aimed at regulation optimization; zero otherwise.
Tech_Dev	The index of overall bank technological development at time t calculated as a sum of existing solutions in a bank at time t.
Tech_Sharing	Number of the same technology provider shared with other banks in a bank i at time t
Fintech_Num	Number of fintech companies in a country of a bank's headquarter at time *t*. Source of the data: Fintech Atlas.
GoogleTrend	A variable which indicates the intensity of a bank name search volume. It is collected monthly and averaged yearly. It ranges from 0 to 100, with higher values indicating increased search. Source: Google Trends
C. ***Macro variables***	
GDP_Growth	Growth of a country's GDP
Inflation	Consumer price index (%)
Concentration	Asset concentratio of the largest 5 banks in a country

Figure A1: Role of bank technological development on NPLs

The Figure presents the estimated coefficients and their confidence intervals using the dynamic DID regression for a treated group of banks having adopted one and two technological solutions. The control banks are non-digitalized banks. The treatment period starts in 2011. For 2018 and 2019 there were no banks that had between 1 and 2 solutions, therefore these years are omitted from the regressions.

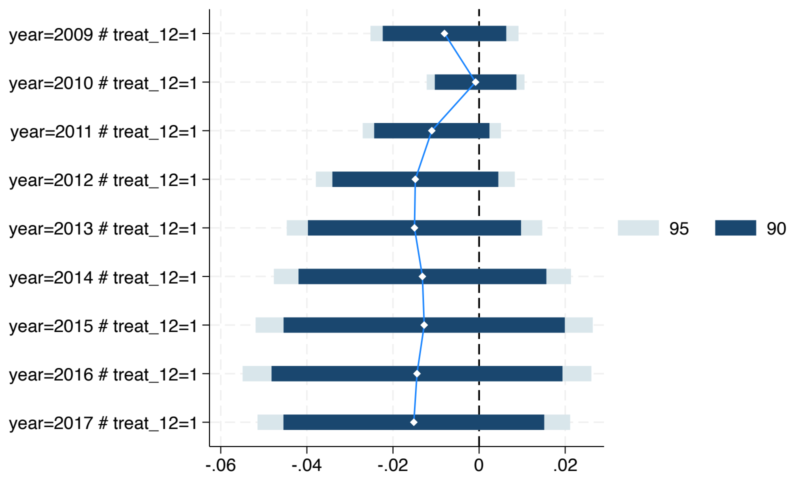

Figure A2: Role of Fintech solutions on banks' NPLs

The Figure presents the estimated coefficients and their confidence intervals using the dynamic DID regression for a treated group of banks having adopted three and four technological solutions. The control banks are non-digitalized banks. The treatment period starts in 2011.

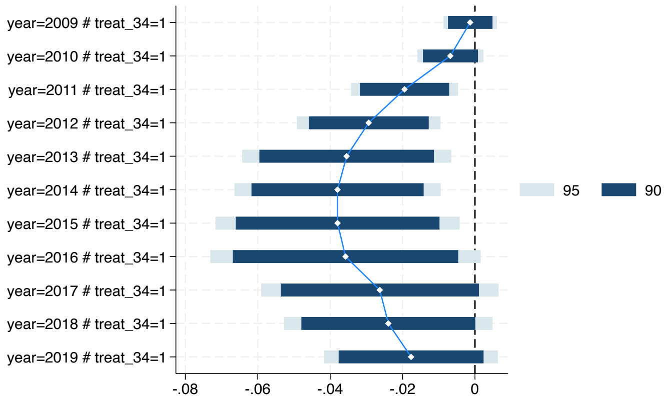

Figure A3: Role of technological innovation on banks' NPLs

The Figure presents the estimated coefficients and their confidence intervals using the dynamic DID regression for a treated group of banks having adopted five and six digital solutions. The control banks are non-digitalized banks. The treatment period starts in 2011.

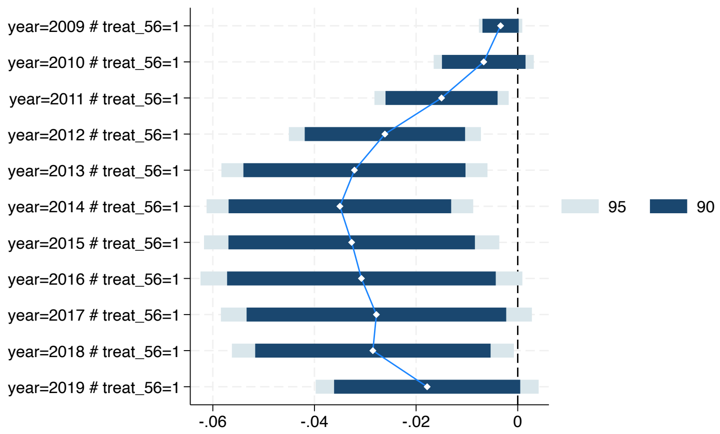

Table A2: Role of technological innovation on banks' business model

The Table presents the regression results using the staggered DID for a treated group of banks having adopted a specific technological solution in a given year; zero for all other banks. The regression results include bank controls such as: Size, Efficiency, ROA, Credit_Activity, TIER1 and country controls include GDP_Growth, Inflation and Concentration, not reported in the Table. All regressions include bank, time and country-time fixed effects, depending on the specifications. Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * p < 0.1, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) InterestMargin	(2) InterestMargin	(3) InterestMargin	(4) InterestMargin	(5) InterestMargin	(6) InterestMargin	(7) InterestMargin	(8) InterestMargin
L.Automation	-2.253							
	(3.566)							
L.Blockchain		0.686						
		(3.322)						
L.Robo_Adv			-0.835					
			(4.278)					
L.Analytics				-1.643				
				(3.178)				
L.Online_Lending					-6.884			
					(4.552)			
L.Electronic_Payment						-7.122***		
						(2.568)		
L.Personal_Fin							6.446	
							(6.535)	
L.Reg_Tech								4.004
								(3.337)
Observations	296	361	265	293	258	392	258	285
R-squared	0.881	0.814	0.814	0.824	0.815	0.859	0.813	0.847
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
TIME-COUNTRY FE	YES	YES	YES	YES	YES	YES	YES	YES

Table A3: Role of technological innovation on banks' business model

The Table presents the regression results using the staggered DID for a treated group of banks having adopted a specific technological solution in a given year; zero for all other banks. The regression examines the effect of bank-specific technology adoption on changes in the share of non-interest income in operating income. The model includes bank controls such as: Size, Efficiency, ROA, Credit_Activity, TIER1 and country controls include GDP_Growth, Inflation and Concentration, not reported in the Table. All regressions include bank, time and country-time fixed effects, depending on the specifications. Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * p < 0.1, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) NonInterest Income	(2) NonInterest Income	(3) NonInterest Income	(4) NonInterest Income	(5) NonInterest Income	(6) NonInterest Income	(7) NonInterest Income	(8) NonInterest Income
L.Automation	2.984							
	(2.914)							
L.Blockchain		-0.0202						
		(2.023)						
L.Robo_Adv			6.572					
			(4.290)					
L.Analytics				0.172				
				(2.371)				
L.Online_Lending					0.354			
					(2.493)			
L.Electronic_Payment						2.076		
						(1.868)		
L.Personal_Fin							2.473	
							(4.243)	
L.Reg_Tech								-0.416
								(2.320)
Constant	-88.40	30.09	5.873	8.873	-116.2	2.852	-80.72	-77.67
	(118.4)	(116.6)	(184.7)	(178.2)	(150.6)	(109.7)	(158.9)	(165.6)
Observations	296	361	265	293	258	392	258	285
R-squared	0.672	0.530	0.523	0.525	0.559	0.556	0.586	0.530
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
TIME-COUNTRY FE	YES	YES	YES	YES	YES	YES	YES	YES

Table A4: The Propensity Score Matching

PSM compares digitalized and non-digitalized banks with similar observable pre-treatment characteristics. Digitalized banks are defined as institutions implementing at least four technological solutions (High_Adopters), while the control group includes banks with no technological solutions (Specifications (1)-(3)). In an alternative specification, we expand the control group to include additionally low-digitalized banks (Specifications (4)-(6)). Propensity scores are estimated using a probit model, where the likelihood of digitalization is regressed on key pre-treatment characteristics. The regression model includes bank controls such as: Size, Efficiency, ROA, Credit_Activity, TIER1 and country controls include GDP_Growth, Inflation and Concentration, not reported in the Table. Finally, we regress the matched banks on lending volume, interest income scaled by operating income, and non-interest income scaled by operating income to evaluate the impact of digitalization on potential shifts in business models.

VARIABLES	(1) Credit_Activity	(2) Interest_Income	(3) Noninterest_Income	(4) Credit_Activity	(5) Interest_Income	(6) Noninterest_Income
Unmatched	-16.355***	-0.223***	7.070***	-2.997***	-0.085***	1.567***
	(2.639)	(0.066)	(2.680)	(4.167)	(0.120)	(5.110)
Matched (ATT)	-1.036	-0.120	3.361	12.444	0.158	-5.672
	(4.010)	(0.097)	(4.200)	(2.870)	(0.160)	(8.001)
Time FE	YES	YES	YES			
Country FE	YES	YES	YES			
TIME*COUNTRY FE				YES	YES	YES
Observations	267	267	267	65	65	65
R-squared	0.127	0.042	0.026	0.086	0.030	0.024