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Navigating the Digital Frontier:

Unraveling the Impact of Bank Technology Innovations on Idiosyncratic and Systemic Risks

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Abstract

The recent development of technological innovation in the banking sector has the potential to bring numerous benefits, but it also raises concerns regarding financial stability, an aspect that has been relatively understudied in academic literature. Our research paper aims to explore the impact of banks' recent adoption of FinTech solutions on both individual and systemic risks within the banking sector. Specifically, we examine how banks' technological innovations influence non-performing loans (NPLs), asset correlation in the system, and measures of systemic risk. To accomplish this, we utilize a unique dataset generated through data mining techniques, which captures the scale, types, and sources of technological solutions implemented by the largest banks in 23 countries over an 11-year period. Our findings indicate that FinTech solutions implemented by banks reduce both individual and aggregated systemic risks in the banking sector, although there are certain areas where systemic risk increases.

Keywords: Fintech, innovation, IT technology, IT providers, bank, systemic risk, NPLs,

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

1. Introduction

Recent estimates by Forrester's Technology & Innovation North America (FORR) suggest that global technology spending is projected to surpass USD 4 trillion in 2023. Despite economic uncertainty, two-thirds of technology decision-makers are increasing their technology budgets. Furthermore, global investments in DeepTech and Fintech have already exceeded 110 billion GBP and 220 billion USD, respectively, in 2021. These figures highlight the substantial growth and significance of the ongoing technological transformation across various sectors, with the banking industry being a notable beneficiary of technological advancements.[1]

The undeniable positive impacts of technological development in the financial sector have been widely recognized. However, the potential risks associated with digitalization remain uncertain and require further investigation. In light of this, our research aims to contribute to the understanding of these risks by examining the impact of technological innovation, specifically financial technology solutions – Fintech, implemented by banks – on the identification and analysis of different sources of risk in the banking sector.

Specifically, our study focuses on three key areas: non-performing loans (NPLs), asset correlation within the banking system, and the resultant impact on aggregated systemic risk measures. By investigating how recent bank Fintech solutions influence these factors, we aim to provide valuable insights into the potential risks introduced by banking sector digitalization.

The impact of financial technology on banking sector risk is complex and multifaceted. The newest technology gives banks access to more accurate and timely data on borrowers and markets. This wealth of data enables banks to improve their assessment of credit risks, leading to more informed lending decisions. By better understanding the risks associated with borrowers, banks can potentially reduce the likelihood of loan defaults and contribute to financial stability (Angelini et al., 2008; Khandani et al., 2010; Berg et al., 2020; Huang et al., 2021). Moreover, Fintech innovation can foster specialization in banking by enabling institutions to reach previously underserved clients (Jagtiani & Lemieux, 2018; Cornelli et al., 2023). This can allow banks to implement more effective screening processes, enhance monitoring mechanisms, and mitigate the adverse selection problems that can arise in the lending process (Winton, 1999; Marquez, 2002; Acharya et al., 2006; Jahn et al., 2016).

At the same time, the recent technological innovation introduces the potential for increased systemic risk by fostering complexity and interdependencies within the financial system. The

[1] https://www.jpmorganchase.com/news-stories/tech-investment-could-disrupt-banking

growing reliance of banks on decision algorithms poses risks when these algorithms rely on shared data or decision patterns (FSB, 2019) This complexity is further compounded when these algorithms originate from the same technology providers. Anecdotal evidence reveals that nearly 90% of technological solutions implemented by U.S. banks are procured from external companies (Cornerstone Advisors, 2021). Moreover, recent data indicate a concentrated landscape of technology providers within the banking sector. For instance, prominent technology giants such as Amazon, Microsoft, and Google dominate approximately two-thirds of the cloud market in the United States.[2] Notably, our data confirm that several major banks, including Goldman Sachs, JPMorgan, and Morgan Stanley, heavily rely on the same technology companies, such as ICapital Network and Kensho, for robo-advisory solutions and data analytics software.

Currently, the technological development of the banking sector remains somewhat of a black box. While there is a growing body of literature exploring bank digitalization, much of it relies on broad measures that fail to capture the specific technological innovations employed by banks, particularly in terms of algorithmic decision-making and its source of origination. Existing studies often either utilize very general measures as IT expenditures or the number of computers which are proxies for a general level of bank digitalization rather than technological development (Beccalli, 2007; Bloom et al., 2012; Branzoli et al., 2021; Bresnahan et al., 2002; Timmer et al., 2021). A few papers analyze the effect of some specific technologies as the introduction of the interbank payment system (SWIFT), ATM, online webpages, mobile applications or access to internet as proxies for bank digitalization (D'Andrea & Limodio, 2023; Hannan & McDowell, 1987; Hernández-Murillo et al., 2010; Scott et al., 2017; Xue et al., 2011; Core and De Marco, 2023). To the best of our knowledge, none of the existing studies have thoroughly examined the recent technological innovation employed in bank decision-making processes, specifically those related to algorithmic decisions. The literature on Fintech institutions documents that many recent technological innovation including the footprints, mobile payments, big data analytics or AI solutions revolve around information processing capabilities and have the potential to significantly influence decision-making processes (Bazarbash, 2019; Berg et al., 2020; P. Ghosh et al., 2021; Jagtiani et al., 2021; Ouyang, 2022). However, we lack a comprehensive understanding of the nature, source, and scale of the Fintech solutions being implemented by banks as compared to the Fintech sector itself. Chen

[2] https://www.statista.com/chart/18819/worldwide-market-share-of-leading-cloud-infrastructure-service-providers

et al. (2019) have conducted a comprehensive study on Fintech innovation, focusing on the types of services offered by these institutions in the US while Lerner et al. (2021) analyze the nature of patent application in the financial technology sector. We extend these studies by conducting a similar analysis but focusing on the impact of technological solutions and services specifically implemented at banks.

Our study aims to fill the existing gap in the literature by analyzing the latest technological development at 363 European and US banks between 2009 and 2019. We start our analysis with a sample of 63 largest banks for which we have collected very detailed data on all technological solutions implemented at these banks over our sample period. We also identify the source of the technology adoption, including information on whether the technology has been purchased, developed in-house, or outsourced. To gather this data, we utilize both Crunchbase and Cbinsights (including *Aberdeen Technology*) databases and employ data mining techniques to scrap webpages and social media for information on technological innovations adopted by banks. Our data document that banks use the following technological innovations: *automatization, blockchain, data analytics, online lending, mobile payments, personal finance, and regulatory technology*. Moreover, our data highlights a significant trend, revealing that over 40% of the largest banks in our sample are dependent on external providers for their technological solutions. This observation aligns with previous research conducted by Lerner et al. (2021) and industry reports, which have consistently highlighted that the majority of financial technology patents originate from technological firms such as Fintechs, DeepTechs, or BigTechs, which are then purchased or outsourced by the banks. Our data also reveal a significant concentration among technology providers who offer specific solutions to large banks. This indicates that a relatively small number of technology providers dominate the market and serve as primary sources for the technological needs of major banks.

To examine the impact of Fintech solutions on banks' individual risk, we employ a static and dynamic difference-in-differences (DID) regression framework that incorporates, among bank and country variables, bank- and time-fixed effects. This methodology enables us to isolate the specific effect of technological innovations on risk by comparing the changes in risk levels over time between banks that have adopted such innovations and those that have not, overcoming potential endogeneity issues.

Our findings provide empirical evidence supporting the positive impact of Fintech solutions adopted by banks on credit risk assessment in the banking sector. Specifically, we observe that banks that have undergone significant technological development processes after 2010 exhibit lower levels of non-performing loans (NPLs) compared to less digitalized banks, as well as to the pre-technological periods. Furthermore, our results reveal that the relationship between bank technological development and NPLs becomes more significant as its level, measured by the number of technological solutions adopted, increases. This suggests that a higher degree of technological innovation and integration in banks is associated with even greater improvements in credit risk assessment and management. These findings align with prior research conducted on Fintech institutions by Angelini et al. (2008), Khandani et al. (2010), Wall (2018), and Huang et al. (2021), which have demonstrated the effectiveness of technological innovations in enhancing credit risk assessment compared to traditional models. Additionally, our results are consistent with the findings of Pierri and Timmer (2022), who observed that banks with a greater number of computers, serving as a proxy for bank digitalization, experienced lower levels of NPLs during the global financial crisis.

Addressing the concern regarding the potential increase in systemic risk due to a greater usage of algorithmic decisions that might rely on similar decision patterns, we start with the synchronicity regression inspired by Chan et al. (2013). The authors analyze how individual company stock features depend on the whole market. By applying a similar methodology, we investigate how various factors such as non-performing loans (NPLs) and TIER1 ratio (the main determinants of systemic risk measures) correlate across different banks based on their level of technological development. Our preliminary observations document that a greater number of technological solutions at banks is associated with lower synchronicity in risk indicators compared to non-digitalized banks. In some instances, our analysis reveals that more digitalized banks exhibit a significantly lower level of co-movement in their risk indicators compared to less digitalized banks. This finding suggests that the degree of technological development within a bank is associated with a reduced correlation among different risk indicators, indicating a more diversified and independent asset allocation strategy across these banks, which can contribute to a reduction in systemic risk.

To provide formal support on the link between bank technological development and systemic risk we utilize a two-way fixed-effect estimator using widely popular SRISK indicators (Acharya et al., 2012; Acharya et al., 2017; Adrian & Brunnermeier, 2016; Brownlees & Engle, 2017). Our estimation results prove that the adoption of technological innovation by banks decreases the overall level of systemic risk. Specifically, our findings suggest that each additional technological solution implemented by a bank decreases potential losses by an estimated 3 billion USD. In economic terms, given that the average SRISK value is 25.74 billion dollars, a decrease of 3 billion USD represents a reduction of approximately

11.7% in SRISK measure from its mean value. This implies that technological solutions adopted by banks have a substantial economic impact on SRISK: each additional solution reduces the systemic risk by about 11.7% from its average level. Furthermore, our analysis uncovers a notable heterogeneity in the impact of individual technological solutions on risk reduction within the banking sector. Specifically, we observe that payment solutions have the largest impact in decreasing risk, while data analytics solutions exhibit the lowest impact. The result is not surprising, as other research documents a high predictive power of payment data on credit risk assessment (Oyang, 2022).

We also explore how the source of technological adoption by banks affects systemic risk. This would be in line with our hypothesis that technologies stemming from external providers may share the same data pattern leading to more correlated decisions in the system (FSB, 2019).

Our regression results document that bank technology stemming from purchases seems to have a declining effect on systemic risk as compared to other sources of its adoption. By selecting technology solutions from various providers, banks seem to focus on specific segments or areas that may be uncovered or underserved by their competitors. This strategic decision-making process allows banks to tailor their technological solutions to their unique needs and business models, potentially reducing overall systemic risk. Alternatively, the effect might capture the diversity of technologies that banks purchase versus deciding to develop in-house, which could provide a diversification effect in the system. However, when we account for the same technology providers across banks, a contrasting trend emerges. We observe that the presence of shared technology providers leads to an increase in systemic risk. This finding seems to support the hypothesis that when multiple banks rely on the same technology provider, offering the same type of service, there may be a higher likelihood of shared decision patterns and interdependencies. This, in turn, can amplify the potential systemic risks within the system.

We are aware that the endogeneity between bank risk and technological development might be a concern. Therefore, in the robustness section, we employed a two-stage least squares (2SLS) instrumental variable (IV) regression. In this approach, we utilize the number of branches, number of patents, and filings for a patent submitted by a bank, along with the level of Fintech credit provided in a country, as potential instruments to measure technological development at banks.

These variables are chosen to ensure that they are not related to any bank-specific operations or features while capturing the potential bank digitalization effect. Our IV regressions demonstrate the robustness of our results proving that better technological development leads to a substantial decrease in bank non-performing loans while the statistical tests seem to confirm the validity of the instruments used in our analysis. Consequently, our analyses document that endogeneity should not bias our regression results.

Furthermore, to enhance the robustness of our analysis, we expand our sample to include an additional 300 banks. In doing so, we employ a proxy for bank technological innovation by examining the share of intangible assets (excluding goodwill) in the total assets of these banks. By incorporating this alternative measure of bank technological development, we aim to verify and validate the results obtained from our initial sample, while also capturing the fact that the majority of bank technology is purchased from Fintech and DeepTech firms rather than developed by banks in-house. These regression results confirm the robustness of our so-far results, ensuring the reliability of our main findings.

Our paper contributes significantly to the existing academic literature. Firstly, we provide a more accurate and comprehensive analysis of the recent technological developments at banks. Unlike previous studies that may have used variables measuring the general digitalization process (as:(Bloom et al., 2014; Brynjolfsson, 1994; Ferri et al., 2019; Fuster et al., 2019; Pierri & Timmer, 2020), we specifically track and analyze the precise technological innovation, within recent Fintech solutions implemented by banks. This level of granularity allows for a more detailed understanding of the specific technologies being utilized by banks in their decision and credit risk processes. Furthermore, our study stands out by not only identifying the technological solutions but also tracking their source of adoption. In addition, our approach also goes beyond pure bank technological development as it also covers how the technology is provided. In this way, it extends the current studies by matching each bank with the technology provider and specific bank product. This enables us to assess the concentration of technological providers within the banking industry. By examining the concentration of providers, we can uncover potential patterns and implications regarding the bank's reliance on the same decision patterns and data sharing within the banks. According to our knowledge, our analysis represents the first in-depth exploration of this research area.

Secondly, we aim to contribute to the academic literature by examining the risk of bank technological development, which has been largely overlooked in previous research. While prior studies have focused on the positive impact of financial digitalization, including improved bank regulatory efficiency (Philippon, 2015), faster loan-decision processing (Fuster et al., 2019; Beaumont et al., 2022), better credit risk assessment ((Berg et al., 2020; Gambacorta et al., 2020; Khandani et al., 2010) or increased access to financial services (Jagtiani & Lemieux, 2018; Huang et al., 2021; Hryckiewicz et al., 2022; Bazarbash, 2019), we specifically address the bank risk and its nature related to both recent technological development but also broader ecosystem in which banks operate. By tracking all recently adopted technological solutions at banks and their sources of adoption, our research enables us to delve deeper into the identification and analysis of different types and sources of risk. This level of granularity in our approach allows us to gain valuable insights into the potential risks associated with specific technological solutions and their origins which have been not studied so far.

Thirdly, the increasing reliance of the banking sector on algorithmic decision-making raises concerns about the potential correlation of the decisions either as a result of the same decision patterns or the concentration of the technology providers. Although the academic literature has addressed and tested concerns about algorithmic trading and its impact on systemic events in the stock market, such as in studies by Jain et al. (2016); Malceniece et al. (2019) or Paulin et al. (2019) our study provides a unique contribution by examining the impact of algorithmic decisions in the banking sector and analyzing its effect on bank asset allocation and its link with the systemic risk.

The paper is divided into four sections. In the next section, we discuss the data on the digitalization trend in the banking sector and associated measures of risk. Section three discusses the Methodology for our study. Section fourth discusses the results while the last section concludes the paper and provides policy implications.

2. Data

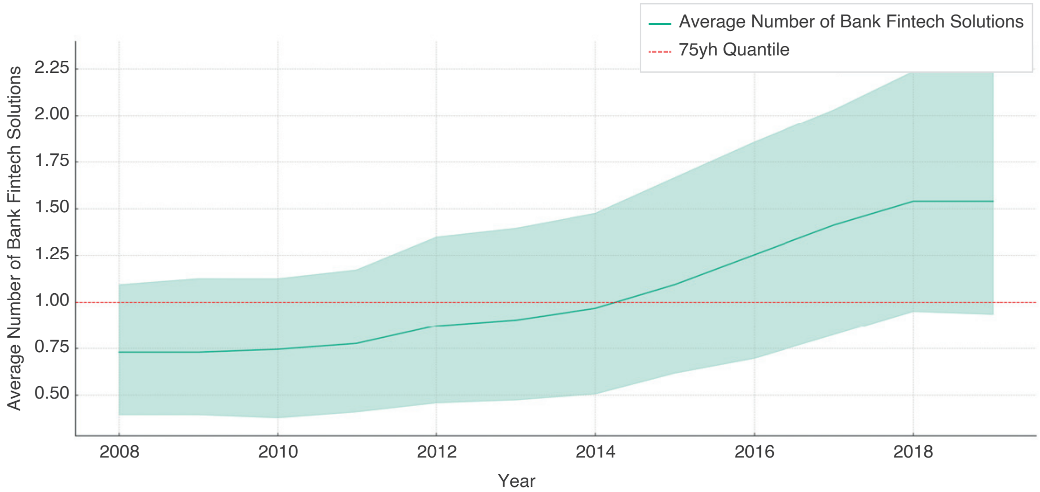
2.1. Digitalization Data

We analyze the impact of bank technological development on idiosyncratic and systemic risks in the banking sector. We start by using a unique database of the 63 largest European and US banks. Our database includes information on the type and year of implementation for each technological solution adopted by these banks between 2008 and 2019. Our definition of technological innovation is broad, encompassing the latest front- and back-office solutions such as automation software (AUTOMATIZATION), blockchain technology (BLOCKCHAIN), data analytics (ANALYTICS), lending solutions (ONLINE_LENDING), payments (MOBILE_PAYMENT), personal finance (PERSONAL_FIN), robo-advisory (ROBO-ADV) and regulatory technology (REG_TECH). We start our analysis by accumulating the number of solutions adopted by banks as a measure of a bank's general technological development (TECH_DEV). In further analysis, we also test how individual solutions translate into banks' risk by indicating them as binary variables equaling one for all years following a bank's adoption of the specific technological solution, and zero otherwise.

We obtain our data from Crunchbase and CBInsights (including *Aberdeen Technology*) databases, supplemented with data-mining techniques that include banks' technological purchases and development announcements on bank social media and in the notes to financial statements. Consequently, our data set is very granular and seems to capture all possible solutions adopted by banks over the analyzed sample periods.

In **Figure 1** we depict the trend of bank digitalization using the TECH_DEV variable over the years.

Figure 1: Bank technological development over the years
The graph shows the trend of bank digitalization over time, specifically focusing on the average number of Fintech solutions adopted by banks. The red dashed line represents the 75th quantile, indicating a benchmark where the top 25% of the data points are above this line. The green area represents the 95% confidence interval.

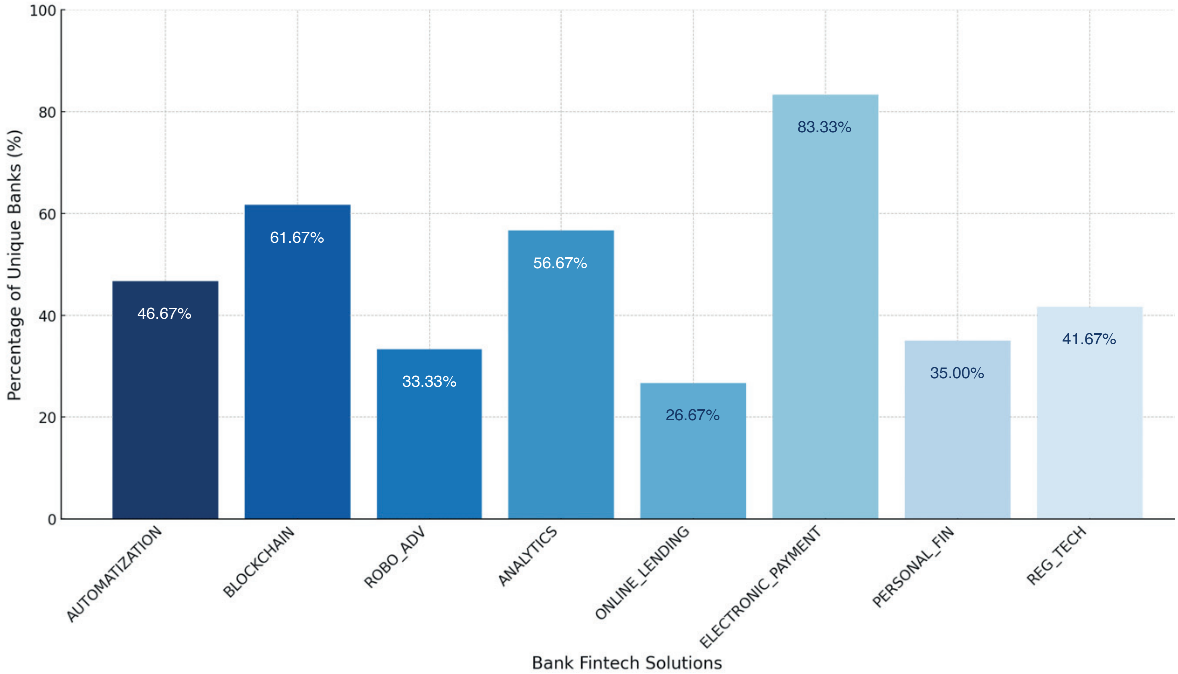


Source: Own data

The data suggests that bank digitization remained relatively constant until 2010, after which it began to increase. This shift coincides with the observation that banks started mainly adopting technological solutions after the global financial crisis. The widening confidence interval and distribution around the bank digitization variable support the notion of a changing landscape, pointing toward a selection of 2011 as the start of the digitalization trend in the banking sector in our sample. Additionally, our data reveals heterogeneities in technological development among banks within the sample timeframe (2011-2019).

Figure 2 we present the distribution of individual technological solutions implemented by banks in our database.

Figure 2: Percentage usage of bank fintech solutions

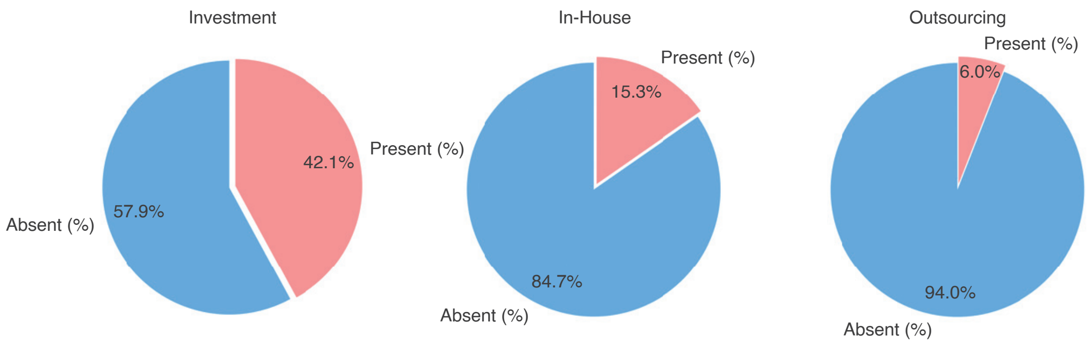


Source: Own data

More specifically, the data from **Figure 2** 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. At the same time, the authors document that most filed patents come from technological companies as DeepTechs, Fintechs or BigTechs but not banks themselves. This observation allows us to conclude that the main source of banks' technological development should come from external providers.

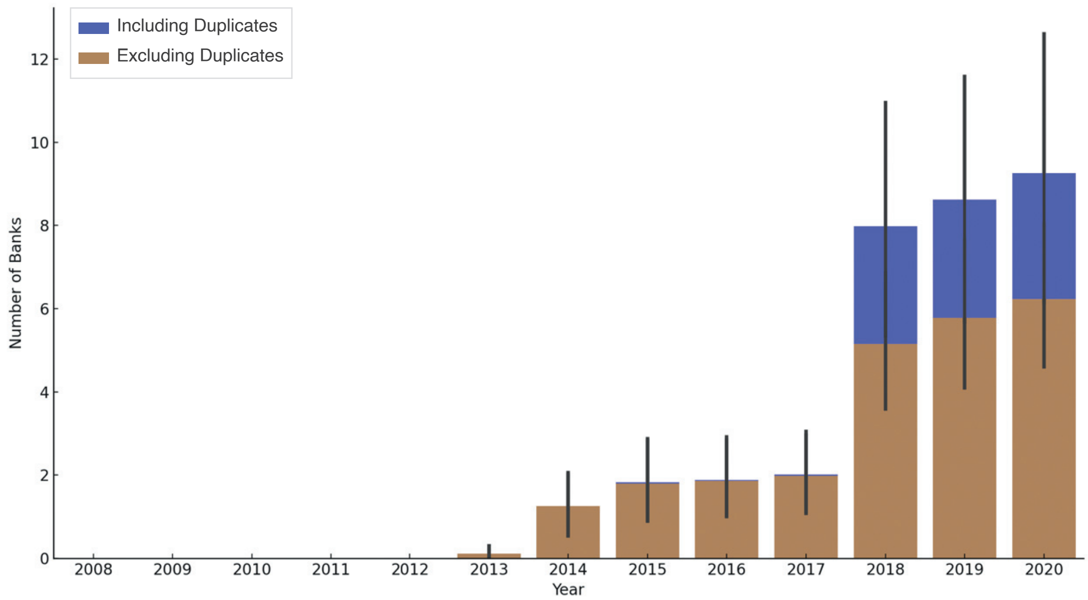
To verify this assumption at the bank level, we match bank technological solutions with the source of their providers. In addition, we also capture the scale of banks sharing the same technological provider which might affect potential systemic risk due to a higher correlation of banks' decisions using the same data or algorithmic patterns. **Figures 3 and 4** show the scale of different solution providers as well as the scale of the same technology providers used by individual banks.

Figure 3: The percentage share of banks using the specific source of technology provider
Each chart corresponds to one of the three categories. The segments represent the proportion of banks having a specific source of technology provider ("present") or not ("absent").



Source: Own data

Figure 4: 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. Duplication here means that some banks might be using multiple solutions from the same provider.



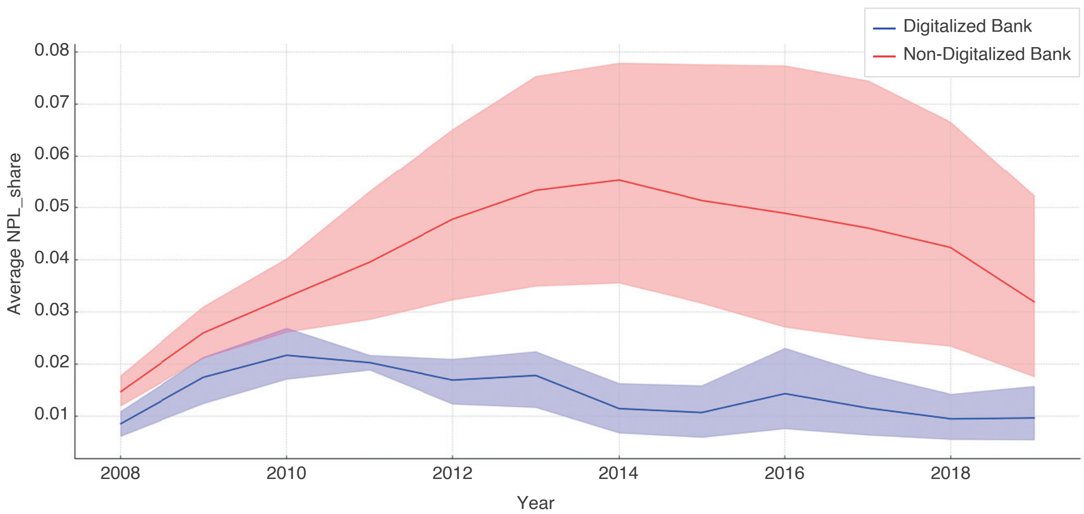
Source: Own data

We notice that the majority of banks use external providers for the adoption of their technologies while only 15% decided to develop technology in-house. We notice that the overall number of banks using the same providers has significantly, increased, especially, between 2013 and 2019. This indicates a greater concentration in the banking industry's choice of technology providers, suggesting that certain providers might have become dominant tech companies. Additionally, we also find that banks also increased the number of products stemming from one provider in recent years. This analysis seems to shed the first light related to the specialization of services provided by a few technology market players for the most systemic institutions.

2.2. 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 are often the harbingers of a banking crisis (Ghosh, 2015; Homar and van Wijnbergen, 2017; Hryckiewicz et al, 2023). **Figure 5** presents the level of bank NPLs over the periods while splitting banks depending on the number of implemented technological solutions.

Figure 5: Trend of non-performing loans (NPL_Ratio) over time between two groups of banks
The trend lines present the development of NPLs over different years for digitalized banks (the number of Fintech solutions is higher than 4) and for non-digitalized banks (the number of Fintech solutions is zero).



Source: Own data

We can notice that before 2011 the level of bank NPLs was evolving in the same direction. This seems to coincide with the period of systemic shock which affected all banks in the sector. However, since 2011 the level of bank NPLs started to diverge between different banks. This seems to coincide with the general improvement of the situation in the banking sector and the start of digitalization in the financial sector. This observation is pivotal, as it provides a rationale for why you might expect the parallel trend assumption across banks' NPLs to break post-2010.

To measure the systemic risk we use SRISK to examine the bank’s contribution to system-wide distress (Laeven et al., 2016). SRISK is defined as a bank's contribution to the deterioration of the financial system's capitalization during a market downturn (Acharya et al., 2012; Acharya et al., 2017; Brownlees & Engle, 2017; Engle et al., 2012). It indicates a bank's capital shortfall caused by a severe market decline (forty percent in a six-month period), with the prudential capital requirement set at 8% for all firms in the sample.[3] Positive values for SRISK imply a capital shortfall, while negative values indicate a capital surplus (no distress). Thus, a bank is systemically risky if it is likely to face a capital shortage just when the financial sector itself is weak (Acharya et al., 2017). We compute SRISK expressed in absolute values as the capital shortfall in USD (*SRISK*) as well as in relative terms (% drop in the capital). In the case of the latter, we calculate the proportional contribution of each bank's SRISK to the total positive SRISK of the financial system (*SRISK%)* (Brownlees & Engle, 2017).

[3] A detailed description of the SRISK is provided by Acharya et al. (2016).

3. Methodology

Banks' technological development is a very complicated and ambiguous process. Banks may invest in technology for various reasons, i.e., to strengthen their relationship with clients (Mullan et al., 2017), become more competitive (Grandon and Pearson, 2004; Cao et al., 2018), or increase efficiency (Lee et al., 2021). Therefore, the reasons to adopt specific technologies might be related to banks' specific business models or strategies banks may want to follow. At the same time, the investment in IT may be determined by bank financials, for example, bank profitability or capital level that may be correlated with the level of non-performing loans. This, in turn, may create a source of endogeneity for modeling the casual relationship. We try to address these endogeneity challenges in our applied methodologies, at the same time providing some checks in the Robustness Section.

We start our analyses by running the multinomial logit and ordered probit regressions to examine how banks' level of technological development depends on their features. This analysis allows us to partially detect the potential endogeneity sources. It would also allow us to analyze how bank technological innovation is related to other banks' characteristics which potentially could influence the causal effect between technology and risk level. We measure a bank's level of technological development in two ways. First, we denote the total number of solutions (TECH_DEV) adopted by a bank in a particular year which we aim to explain by using the multinomial probability model. Alternatively, we also use the ordered probit model which allows us to explain every number of solutions adopted by banks. Consequently, the models take the following form:

$$\mathbf{P(Y_{it}=TECH\_DEV_{it})} = \beta_0 + \beta_1 X_{it-1} + \beta_2 Z_{jt} + \alpha_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

where X_{it-1} denotes the bank's specific variables as: asset size (Size), bank profitability (ROA), TIER1 capital ratio (TIER1_Ratio), net loans to total asset (Credit_Activity), cost to income (Efficiency), NPL ratio (NPL_Ratio), non-interest income to total income (NonInterest_ Activity*),* deposit to loans ratio (Liquidity). We lag the bank control variables by one year to address the potential reverse causality. Z_{jt} denotes country j variables as: GDP growth and inflation in a year t. Since probability models have been documented to be biased while using individual fixed effects (Neyman & Scott, 1948), we only include the time-fixed effect across our other control variables.

Before we proceed with the DID regression, it is crucial to ensure that the treatment effect has been accurately identified, as it is a requirement for the assumptions of the DID methodology. Given the difficulty of identifying an exogenous shock that affects one group of banks while not affecting others, we include the $TECH\_DEV_{it}$ variable in our regression analysis and interact it with the individual years. This approach enables us to examine whether the start of the bank digitization period aligns with the data in 2011 or occurs in different years. However, it is important to acknowledge that this approach does not fully mitigate potential endogeneity concerns between bank technological development and NPLs. Nevertheless, it does not rely on assumptions regarding the level of bank technological development or NPLs across banks and periods. Consequently, this approach serves as a good starting point to examine whether there is a noticeable shift or break in bank technological development. To do so, we begin by conducting the following regression analyses:

$$\mathbf{NPL\_Ratio_{it}} = \beta_0 + \beta_1 TECH\_DEV_{it} + \beta_2(TECH\_DEV_{it} * YEAR\_DUMMY_t) + \beta_3 X_{i-1t} + \beta_4 Z_{jt} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

To address the potential endogeneity problems related to the fact that a lower level of bank NPLs might already come from a better screening of borrowers before our treatment period, i.e. before banks have experienced significant technological growth, we apply two-way fixed-effect difference-in-difference (DID) estimator. It allows us to compare a bank's NPL level before and after treatment periods as well as across different groups of banks which has been already indicated by our data. We control for time-fixed effects to control for the effects of a business cycle that could have been important during the financial crisis. Additionally, we control for the bank fixed effects to control for the constant bank characteristics as, for example, bank attitude toward technological development. Our empirical models take either static or dynamic form:

$$\mathbf{NPL\_Ratio_{it}} = \beta_0 + \beta_1 Treatment\_Years_t + \beta_2 HighDigital_{it} + \beta_3(Treatment\ Years * HighDigital)_{it} + \beta_3 X_{i-1t} + \beta_4 Z_{jt} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (3)$$

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; X_{it-1} denotes the bank-level variables as defined in the probability regressions 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.

Banks can either be assigned to a treated or control group. In our methodology, we allow banks to enter the treated sample after 2010 only when the number of solutions adopted by a bank in a given year exceeds four which was the median over the whole sample. We refer to these banks as "*high technology adopters*" (HighDigital). Banks with no solutions enter our control group. We set the start of our treatment period for 2011 onwards, as 2008-2010 were the years where both groups of banks were affected by the parallel trend of NPL development due to the systemic shock, as documented in the previous Section.[4] This trend started to diverge in 2011 which we identify as a break year and start our treatment period. The interaction term in Eq. (3) β_3(Treatment_Years*HighDigital) is our key variable of interest. It is an interaction between the post-crises years (after 2010) and a dummy for being a „*high technology adopter*" (i.e. having at least 5 digital solutions). The coefficient β_3 should be interpreted as a unit increase/decrease in the outcome variables associated with being a high technological adopter post-2010.

We also explore the dynamic effect of technological development on bank NPLs by interacting the treated banks with each post-treatment period. This would allow us to notice a change in the effect depending on the time passage. An increase in the magnitude of the negative coefficients would suggest that bank technological development occurring with time passage decreases the level of bank NPLs.

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

$$\mathbf{SRISK_{it}} = \beta_0 + \beta_1 \mathrm{TECH\_DEV}_{it} + \beta_2 X_{it-1} + \beta_3 Z_{jt} + \alpha_i + \lambda_t + \varepsilon_{it} \qquad (4)$$

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 $\mathrm{TECH\_DEV}_{it}$. It allows us to identify the effect of bank technological development on systemic risk measures. Similarly, as in the previous specifications, we define $\mathrm{TECH\_DEV}_{it}$ 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 AUTOMATIZATION, BLOCKCHAIN, ANALYTICS, ONLINE_LENDING, ELECTRONIC_PAYMENT, PERSONAL_FIN,

[4] We have also tested parallel trend assumption required for DID regressions and find that NPLs level of both groups were significantly affected and followed the same trend between 2008 and 2010.

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) by assigning one to those banks that have the same technology provider across their solutions, and zero otherwise.

As in another model, we include bank-and-country controls which have been documented as important determinants of systemic risk. Finally, we also use the bank-and-time fixed effects to control for all potential bank unobservable features that could impact bank contribution to systemic risk. 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. **Table 1** provides the summary statistics for all our variables used in the regressions.

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_ACTIVITY	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_RATIO	626	13.551	3.486	4.3	29.36
NPL_RATIO	639	0.037	0.06	0	0.495
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			
AUTOMATIZATION	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
DEV_TECH	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
		COUNTRY VARIABLES			
INFLATION	756	1.539	1.516	-4.478	15.402
GDP GROWTH	756	1.266	3.031	-14.434	25.176
BANK CONCENTRATION	630	64.085	17.247	34.317	98.867

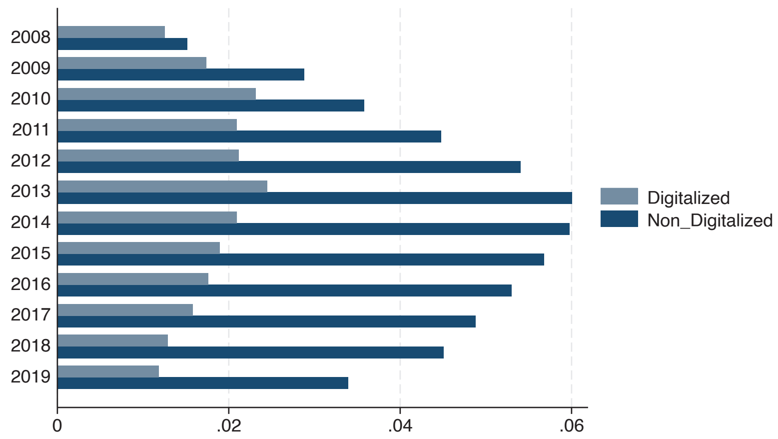
We also provide the definitions of all variables used in our study in the **Appendix in Table A1**.

4. Results

4.1. Univariate analysis

Before delving into our econometric analysis, we first establish a few key stylized facts concerning the relationship between bank technological development, NPLs, and the co-movement among bank risk indicators to shed light on a potential correlation in the system. First, we examine whether banks with higher numbers of innovative technological solutions exhibit a lower NPL_Ratio than other banks. To this end, we divide our bank sample into two groups: a group of banks with any technological solution (Digitized) and a group comprising institutions without any implemented digital solution (Non_Digitalized). **Figure 6** presents the mean of NPLs for both groups of banks across different years.

Figure 6: The average distribution of non-performing loans (NPL_Ratio) among two groups of banks.

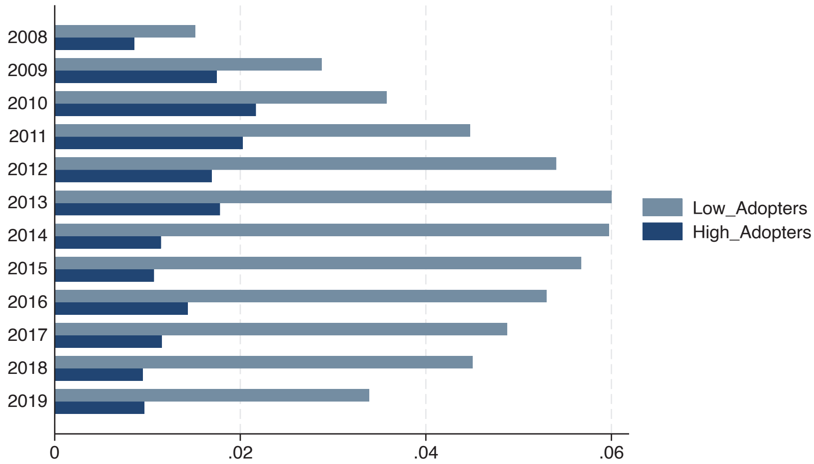


Source: Own estimations

We observe that the mean share of NPLs in the treated group (i.e., banks with any adopted technological solution) is significantly lower, by more than half, compared to the control group (i.e., banks with no adopted technological solutions). Until 2010 both groups of banks were experiencing an increase in the NPL_Ratio while after that period we noticed that the share of NPLs in digitalized banks started decreasing (apart from 2013 when it increased), as compared to non-digitalized banks. At the same time, the share of NPLs of non-digitalized banks was increasing significantly until 2013. In 2019 the NPL_Ratio of digitalized banks reached slightly one-third of the ratio of non-digitalized banks.

However, analyzing NPLs between digitalized and non-digitalized banks may conceal significant heterogeneity across digitalized banks. To address this, we divide banks into "high technology adopters" (the number of adopted solutions is above 4 (over the median) over the sample period) and "low technology adopters" (the number of adopted solutions is lower than 5 (below the median)). **Figure 7** illustrates the distribution of NPL_Ratio among two groups of banks depending on bank technological intensity.

Figure 7: The average distribution of non-performing loans (NPL_Ratio) among two groups of banks.



Source: Own estimations

We observe an interesting trend during the financial crisis (2008-2010) indicating that both groups of banks were experiencing an increase in the NPLs, though the magnitude of this increase was slightly different depending on the scale of bank technological development. However, after 2010, we noticed that more technologically advanced banks were experiencing a downward trend in the NPLs while for less technologically advanced the development of NPLs was mixed. Our analysis shows that in the last year of our study, "*high technology adopters*" had approximately only one-third of the NPLs of "*low technology adopters*".
Before we 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 NPL_Ratio and Equity_Ratio – the main determinants of our systemic risk measure – SRISK. 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 (Bruennermeier et al., 2009; Cannas et al., 2015). 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 8-9** present the regression synchronicity coefficients for NPLs and Tier1 across two groups of banks.

Figure 8: 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 number of bank digital solutions.

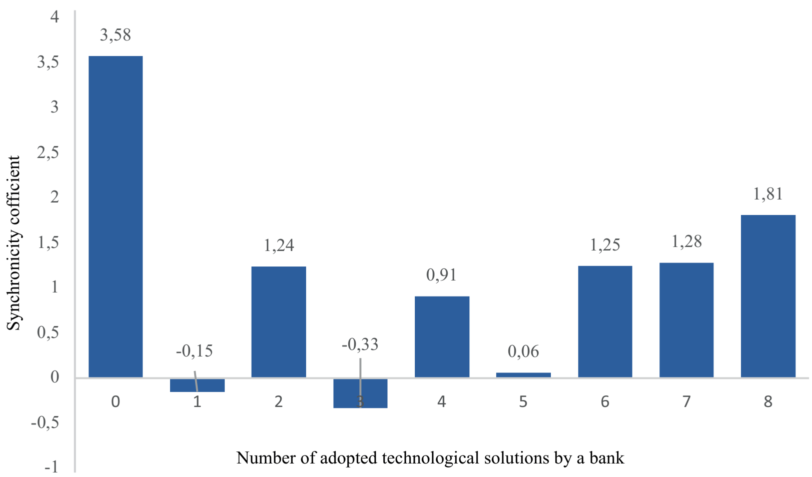
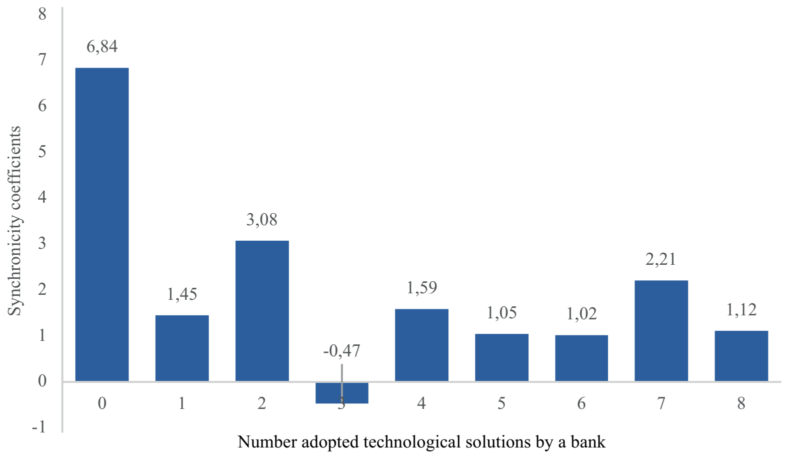


Figure 9: NPLs synchronicity among different banks (N=59)

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 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 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 Equity_Ratio 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 technological innovations seem to reduce the correlation in the system across bank NPLs and Equity_Ratio. These results may suggest that greater technological development leads to 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.

4.2. The determinants of bank technological adoption

We start our analysis with the determination of the factors affecting the level of bank technological adoption. This could shed light on a potential endogeneity problem that might be prevalent in our study, mainly related to the fact that banks exhibiting specific characteristics may have a higher propensity for technological adoption, influencing their NPL_Ratio. **Table 2** presents the regression results for the multinomial logit model (Specification 1) and ordered probit model for the specific number of solutions (Specifications (2) – (5)).

Table 2: Probability Regressions

The first Column presents the regression results using the multimodal logit model to explain the number of solutions used by a bank in a given year. The Columns (2)-(8) present the results using the ordinary probit models to explain each number of solutions adopted by banks. All the regressions include time-fixed effect and the bank- and country time-variant control variables. Standard errors are clustered at the bank-level. Standard errors are in parentheses indicating * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Number of solutions				
VARIABLES/Number of Solutions	**Number of Solutions**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
L1.ROA	0.0300**	-0.00268	0.00668	0.111	0.103**	0.102	0.0319	-0.0159	0.301***
	(0.0123)	(0.00582)	(0.00881)	(0.0679)	(0.0437)	(0.0958)	(0.0576)	(0.0546)	(0.107)
L1. TIER1_RATIO	-0.0630	-0.134	-0.269*	-0.143	0.00459	0.0277	-0.184***	0.590***	0.575**
	(0.0635)	(0.0847)	(0.143)	(0.176)	(0.0963)	(0.106)	(0.0665)	(0.192)	(0.245)
L1. SIZE	0.877**	0.0132	1.599**	1.642**	1.218**	1.206*	1.253	4.766**	1.825**
	(0.382)	(0.563)	(0.731)	(0.648)	(0.589)	(0.696)	(0.821)	(2.005)	(0.736)
L1. LOAN ACTIVITY	-0.0405***	-0.0198	0.0164	0.0210	-0.00655	-0.00737	-0.0101	-0.00379	0.0446
	(0.0155)	(0.0223)	(0.0412)	(0.0569)	(0.0405)	(0.0501)	(0.0426)	(0.0597)	(0.113)
L1. EFFICIENCY	0.0136	0.00870	0.00976	0.0245	-0.0182	0.00722	-0.00929	-0.0151	0.0603
	(0.00879)	(0.0127)	(0.0121)	(0.0189)	(0.0411)	(0.0221)	(0.0317)	(0.0317)	(0.0467)
L1. NPL_RATIO	10.09	-4.164	10.71*	2.614	-10.10	-11.46	-10.77	15.75	3.090
	(7.823)	(5.680)	(6.437)	(6.761)	(18.98)	(22.04)	(19.87)	(19.22)	(11.26)
L1.NONINTEREST_ACTIVITY	-0.00169	0.00909	0.00500	0.00176	-0.000244	0.00268	0.00232	-0.0399	-0.00485
	(0.00903)	(0.0171)	(0.0160)	(0.0299)	(0.0216)	(0.0190)	(0.0245)	(0.0281)	(0.0262)
L1. LIQUIDITY	-0.287	0.220	-0.176	3.116*	1.523	1.363	1.276	2.698	5.004
	(0.561)	(1.095)	(1.208)	(1.863)	(1.030)	(1.296)	(1.224)	(2.070)	(4.404)
GDP GROWTH	-0.107***	0.149***	-0.0157	-0.0646	-0.0974**	0.152	0.219**	0.323*	0.220**
	(0.0406)	(0.0440)	(0.0805)	(0.107)	(0.0452)	(0.120)	(0.106)	(0.185)	(0.0886)
INFLATION	0.200***	0.386	-0.193	0.214	0.357	0.430	0.0769	-0.0457	1.179***
	(0.0711)	(0.269)	(0.147)	(0.246)	(0.223)	(0.319)	(0.178)	(0.343)	(0.341)
CONSTANT		-2.643	-33.28**	-41.01**	-28.30**	-30.37*	-26.27	-110.8**	-66.52**
		(11.46)	(15.46)	(16.38)	(13.51)	(16.07)	(17.14)	(45.05)	(29.38)
Bank FE	NO	NO	NO	NO	NO	NO	NO	NO	NO
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	617	617	617	617	617	617	617	617	617

The regression results suggest that some bank individual characteristics seem to influence bank technological adoption. Specifically, we document that bank size and profitability (ROA) are the most significant factors influencing bank decisions about technology adoption. Interestingly, we do not notice any significant effect of bank NPLs which seems to suggest that bank NPLs do not explain bank technological adoption. Though we notice that lending activity decreases with a higher bank technological development (Specification (1)), however, this could also indicate that banks must choose between lending and technology investment. We do not find this kind of relationship in Specifications (2) and (5) using ordered probit model. Both variables, Credit_Activity and NonInterest_Activity, which serve as proxies for the bank's operational model, are found to be statistically insignificant. This suggests that the bank's adoption of technology appears to be uncorrelated with its business model. Moreover, we also do not find any statistically significant impact of other bank variables. These findings may indicate that the potential endogeneity problem which could be related to the selection bias may not be a serious concern in your study. We will, however, address this problem more formally in the Robustness Section.

5. Bank Technological Development and Risk

5.1. Bank Technological Development and Bank Individual Risk

We start our analysis by exploring the effect of bank technological development on its NPLs across time as well as testing whether we can identify any break in the digitalization trend across banks impacting bank NPLs. In line with the existing studies, recent technological innovation should decrease bank credit risk due to more precise credit scoring techniques, better access to the data, and real-time monitoring of the borrowers (Angelini et al., 2008; Khandani et al., 2010; Jagtiani & Lemieux, 2019; Berg et al., 2020). As mentioned, this approach in contrast to the DID methodology, does not allow us to make any assumption about the NPLs' development across different banks and periods. The results are presented in **Table 3** where columns (1), (2), (3), and (4) present the regression results using different model specifications.

Table 3: The impact of bank Fintech solutions on NPL_ Ratio

The Columns present the regression results using the TECH_DEV as a measure for bank digitalization. TECH_DEV is an index capturing the number of bank's technological solutions each year. It is interacted with individual year dummies (for example, a dummy Year_Dummy2009 takes one for all years starting from 2009 onwards; for years before it takes zero). All regressions include bank- and time-fixed effects. The time dummies are not reported. 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)**
VARIABLES	**NPL_Ratio**	**NPL_Ratio**	**NPL_Ratio**	**NPL_Ratio**
L. TECH_DEV	-0.00282	-0.000680	-0.000762	0.00234
	(0.00258)	(0.00281)	(0.00244)	(0.00240)
TECH_DEV *Year2009		-0.00233		
		(0.00318)		
TECH_DEV *Year2010			-0.00186	
			(0.00148)	
TECH_DEV *Year2011				-0.00390**
				(0.00168)
L1.SIZE	-0.0404**	-0.0399**	-0.0406**	-0.0410**
	(0.0168)	(0.0167)	(0.0167)	(0.0164)
L1.LIQUIDITY	-0.0768	-0.0766	-0.0758	-0.0773
	(0.0512)	(0.0511)	(0.0509)	(0.0497)
L1.PROFITABILITY	-0.00536*	-0.00535*	-0.00529*	-0.00513*
	(0.00279)	(0.00280)	(0.00281)	(0.00281)
L1.EFFICIENCY	0.000143**	0.000143**	0.000143**	0.000150**
	(6.86e-05)	(6.91e-05)	(6.78e-05)	(6.66e-05)
L1.LOAN ACTIVITY	-0.00186*	-0.00187*	-0.00184*	-0.00189*
	(0.00108)	(0.00108)	(0.00107)	(0.00106)
L1.TIER1_RATIO	0.00160	0.00157	0.00157	0.00145
	(0.00147)	(0.00147)	(0.00147)	(0.00146)
GDP GROWTH	0.00225	0.00224	0.00224	0.00225
	(0.00154)	(0.00153)	(0.00156)	(0.00158)
INFLATION	-0.00528	-0.00529	-0.00528	-0.00522
	(0.00532)	(0.00534)	(0.00532)	(0.00525)
Constant	0.894**	0.885**	0.895**	0.906**
	(0.388)	(0.386)	(0.387)	(0.379)
Observations	445	445	445	445
R-squared	0.276	0.276	0.277	0.283
Time FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES

Our main finding from this regression is that the bank digitalization variable doesn't statistically impact NPLs across all years supporting the hypothesis that technological development does not uniformly affect banks' NPLs across all years. This supports our previous observations about the parallel trends in the NPL's development, independently, from the bank's technological level during the crisis period while a deviation from this trend happened afterward when the digitalization period started. The statistically significant coefficient for the interaction with a year dummy 2011 and afterward indicates a start of the deviation from the trend of 2008-2010. Interestingly, we notice that any previous year dummies are not statistically significant in the regression. This supports the observation that the parallel trend holds until 2010 but breaks down afterwards, justifying that an increase in bank digitalization which used to happen after 2010 has affected bank NPLs.

Following these findings, we present the regression results using the DID method where we compare highly digitalized banks to banks that have not implemented any technological solutions (non-digitalized banks). We assume a breakup trend between these two groups of banks after 2010. **Table 4** presents the regression results where columns (1), (2), (3), and (4) present the regression results using different model specifications.

Table 4: The impact of digitalization on bank NPL_Ratio

The Columns present the regression results using the static DID for a treated group of banks having adopted more than four digital solutions (HighDigital) in a given year; zero for banks with no solutions. Interaction is defined as a HighDigital *Treatment_Years where the Treatment_Years are dummies equal to one for the periods between 2011 and 2019. For the years before 2011 they take zero. Bank control variables include Size, Profitability, Efficiency, Credit_Activity, Liquidity, Equity_Ratio. Country controls include: gdp growth, inflation and bank 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**
HighDigital* 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 FE	YES	YES	YES	YES
Time FE		YES	YES	YES
Macro controls			YES	YES
Bank controls				YES

The regression results provide significant and noteworthy insights. Firstly, they reinforce the findings from the quantitative analysis in the previous section, as well as those of other researchers, by showing that technological innovation in finance has a reducing impact on NPLs in banks (Bazarbash, 2019; Berg et al., 2020; Gambacorta et al., 2020; Huang et al., 2021). 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. Since the standard deviation of the NPLs variable is 0.06, these estimates are economically significant, representing a reduction of approximately 33% of the standard deviation. Overall, we can conclude that bank technological innovation helps to mitigate the idiosyncratic risk of banks, which can be attributed, most likely, to better data availability accessible due to different technologies.

For a better understanding of the evolution of the technological development effect over time, we also employ the dynamic DID. Hereby, we analyze how the effect distributes across individual post-treatment years. We present the results for the NPL_Ratio in **Table 5.**

Table 5: The impact of digitalization on bank NPLs level

The Columns present the regression results using the static DID for a treated group of banks having adopted more than four technological solutions (HighDigital) in a given year, and zero for banks with no solutions. Interaction is defined as a HighDigital * Year_Dummy which is equaled to one for a given year and zero for others. Bank control variables include Size, Efficiency, Profitability, Credit_Activity, Liquidity, Equity_Ratio while country controls include: GDP growth, inflation and bank 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**
Year_Dummy2009* HighDigital	-0.00557**	-0.00560**	0.000180	-0.009
	(0.00225)	(0.00225)	(0.0104)	(0.009)
Year _Dummy2010* HighDigital	-0.0080	-0.0082	-0.0026	-0.0145
	(0.0053)	(0.0052)	(0.0108)	(0.0051)
Year_Dummy2011* HighDigital	-0.0187**	-0.0187**	-0.0236**	-0.0236**
	(0.00737)	(0.00740)	(0.00935)	(0.00960)
Year_Dummy2012* HighDigital	-0.0292***	-0.0291***	-0.0370***	-0.0338***
	(0.0100)	(0.0100)	(0.0104)	(0.0113)
Year_Dummy2013* HighDigital	-0.0348***	-0.0348***	-0.0335***	-0.0234*
	(0.0129)	(0.0129)	(0.0110)	(0.0138)
Year_Dummy2014* HighDigital	-0.0366***	-0.0363***	-0.0334***	-0.0279**
	(0.0132)	(0.0132)	(0.00945)	(0.0125)
Year_Dummy2015* HighDigital	-0.0337**	-0.0333**	-0.0357***	-0.0271***
	(0.0147)	(0.0148)	(0.0102)	(0.00950)
Year_Dummy2016* HighDigital	-0.0302*	-0.0302*	-0.0306***	-0.0264**
	(0.0157)	(0.0158)	(0.0105)	(0.0116)
Year_Dummy2017* HighDigital	-0.0266*	-0.0263	-0.0339**	-0.0350**
	(0.0156)	(0.0157)	(0.0153)	(0.0157)
Year_Dummy2019* HighDigital	-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 FE	YES	YES	YES	YES
Time FE		YES	YES	YES
Macroeconomic controls			YES	YES
Bank controls				YES

Interestingly, we notice that the coefficients during the financial crisis period (2008-2010) are statistically insignificant, indicating the absence of any pre-trend existence. Moving beyond this period, we can observe a discernible change in the interaction coefficients. For banks that were in the treated group and adopted innovative technology after 2010, we notice a decrease in the share of non-performing loans. The effect is especially noticeable immediately after 2010, and in general, the effect remains negative in subsequent years. The statistical significance of the regression coefficients supports the impact of innovative technology, with some coefficients being significant at a one percent level and others at a five percent 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 technological development became even more pronounced. These findings suggest that higher levels of bank technological innovation, achieved through the implementation of more innovative technological solutions, can help banks manage their credit risk resulting in a reduction of non-performing loans.

Moreover, our regression results also support the identifying assumption for the Difference-in-Differences model, which states that the treatment and control banks follow a parallel trend before the treatment period, while this trend diverges as a result of the treatment (Angrist & Pischke, 2008). The regression results demonstrate that the interaction terms for HighDigital and the years before treatment (Treatment_Year2008 and Treatment_Year2009) are statistically insignificant, suggesting no significant difference in pre-treatment trends in non-performing loans (NPLs) across the two groups. However, we observe that the coefficients on the interactions involving the years after 2010 become statistically significant for HighDigital banks, indicating an influence of technological development on their level of NPLs. This finding confirms that the banks in the pre-treatment period exhibit parallel trends in NPLs, as required by the DID methodology. Subsequently, these trends start to diverge across banks in the treatment period, i.e., after 2010.

5.2. Digitalization and Systemic Risk

The results of the synchronicity regressions presented in the previous subsection suggest that digitalization may have a positive effect on credit risk reduction in the banking system. However, this does not mean that the aggregated risk in the system goes down. Brunnermeier et al. (2009), Zedda and Cannas (2020), Roncoroni et al. (2021) document that even small losses may magnify the systemic effect if they spread across multiple banks in the system. In this section, we aim to provide a more comprehensive validation of our findings by examining the impact of digitalization on systemic risk measure - SRISK, whilst controlling for other (confounding) factors. **Table 6** presents the regression results for two measures of systemic risk in our sample. Column (1) shows the regressions with SRISK as an absolute measure, while Column (2) shows the same measure expressed as a percentage.

Table 6: The impact of digitalization 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. EQUITY_RATIO	-0.136**	-1.5e+03**
	(0.064)	(593.073)
L1.CREDIT_ACTIVITY	-0.013	66.270
	(0.012)	(111.293)
L1.NONINTEREST_ACTIVITY	-0.005	-53.520
	(0.007)	(62.074)
L1.LIQUDITY	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

The regression results presented in **Table 6** confirm that technological innovation has a negative and statistically significant effect on systemic risk, as indicated by the coefficients of TECH_DEV in both specifications. The economic effects are substantial, with an additional technological solution adoption at a bank resulting in a decrease in systemic risk of $3 billion USD, based on the estimates in columns (1) and (2). This economic effect seems to be significant considering that in March 2009, the systemic risk indicator reached a peak of around $1.1 trillion USD (Huang et al., 2020). Additionally, we find that the adoption of additional technological solutions by a bank results in a decrease in the systemic risk contribution by 0.185 percentage points. These results align with our synchronicity analysis, which indicates that bank technological development leads to lower co-movements among Equity_Ratio and NPL_Ratio. This further seems to suggest that digitalization promotes diversification within the banking sector and contributes to the reduction of systemic risk.

As previously noted, the impact of technological innovations on risk reduction may vary with the type of solution adopted by a bank. Automatization solutions may be less effective in reducing risk, while payment systems and data analytics may improve credit risk techniques and ultimately decrease systemic risk due to the collection and analysis of large amounts of data about the customers. To explore this further, we replace the DEV_TECH variable in our regression models with the type of technological solution adopted by a bank. **Table 7** displays the results of these extended regression analyses. Columns (1)-(6) present the coefficients for AUTOMATIZATION, BLOCKCHAIN, ANALYTICS, ONLINE_LENDING, ELECTRONIC_PAYMENT, ROBO_ADV, PERSONAL_FIN and REG_TECH.

Table 7: The impact of 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: AUTOMATIZATION, BLOCKCHAIN, ROBO_ADV, ANALTYTICS, ONLINE_LENDING, MOBILE_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
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. EQUITY RATIO	-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.LOAN 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.NON_INTEREST	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.DEPOSIT RATIO	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)
AUTOMATIZATION	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

The results of the regressions in **Table 7** indicate a negative and statistically significant impact of adopting BLOCKCHAIN, ROBO_ADV, ANALYTICS, and ELECTRONIC_PAYMENT on the SRISK measures. Among these solutions, MOBILE_PAYMENT appears to have the most meaningful economic effect. This is consistent with recent studies that show that payment data have been widely used and very effective in the improvement of credit scoring models (Ouyang, 2022). On the other hand, the impact of ONLINE_LENDING and PERSONAL_FIN on systemic risk turns out to be statistically insignificant. These results suggest that algorithmic lending decisions do not seem to increase systemic risk. One of the explanations could be that since they are not widely used by banks (see Figures 1 and 2), it does not contribute to the risk effect.

5.3. Technological Providers and Bank Systemic Risk

Systemic risk in the banking sector may increase when banks relying on algorithmic decisions utilize technological solutions from external providers. In such cases, the algorithms may depend on the same data and/or similar patterns. Consequently, the asset allocation strategies employed by these banks might exhibit similar features, leading to a greater correlation within the system. To test how the source of technological adoption affects the SRISK, we run the same type of regressions as in the previous subsection using, among bank-and-country control variables, the bank-and-time fixed effects. Additionally, we map each bank's technology with its source of adoption (in-house development, purchase, or outsourcing of technology). Consequently, we create a dummy that equals one if a bank uses a specific source of solution adoption in a year t (independently, from the technology type); if not, then we indicate zero. We then create an interaction variable between a bank's technological development (TECH_DEV) and the source of technology adoption to explore the heterogeneity in the impact of technology on SRISK, depending on its source. Our hypothesis suggests that the purchase of solutions might lead to more correlated decisions within the system, potentially increasing the systemic risk effect. It is supported by the theoretical consideration by FBS (2019) that technological companies, like Fintech or DeepTech, which provide the technology to banks, may use the same data and patterns to model their decisions. This, in turn, would suggest that banks relying on external technology providers to a greater extent may exhibit a correlation in risk. **Table 8** presents the regression results using two measures of SRISK.

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. 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.NON_INTEREST	-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
Banks	50	50	50	50	50	50
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

Interestingly, our regression results seem to reject the hypothesis that relying on external technology providers may increase the correlation in the system. Our empirical results seem to prove an opposite relationship. They document that the purchase of technology has a negative effect on systemic risk. The effect also seems to be meaningful as the purchase of the technology seems to reduce the systemic risk by almost seven percentage points as compared to other sources of adoption. The result may prove our previous results suggesting that banks tend to purchase solutions to cover specific market niches and differentiate from the competitors. Therefore, they tailor the solutions to align closely with their specific needs and risk management strategies. A greater product range approaching a more diverse group of customers seems to create a diversification effect in the system. Alternatively, the effect might arise from the fact that banks with higher technological development were more likely to rely on purchasing products rather than developing them in-house.

Consequently, our variables for the source of technology adoption may not adequately capture how individual technological solutions, particularly AI solutions, can lead to correlated decision-making among banks. In fact, our regression results indicate that diversity in terms of products and providers is beneficial for the banking system, reducing its risk.

To fully test how different decisions might be interrelated depending on the service and solution provider, it would require a matching process for each bank with the respective solution provider and its type. This would enable us to control for whether the same providers offering the same type of technological product across different banks result in interdependencies in bank investment, thus increasing risk factors. Consequently, we create a variable that measures the total number of common technological providers with a given bank in time t. We call this variable TECH_SHARING. This variable is time-varying as banks' technological development progresses over time. We assume that if a bank *i* shares the same technology with a higher number of banks, there might be a higher correlation in the system if the decision patterns from the same providers exhibit any kind of similarities. **Table 9** provides the regression results.

Table 9: 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.* 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**
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

The regression results provide very interesting conclusions which, this time, are in line with our hypothesis. They find that while controlling for the same technological providers we find that the systemic risk measure in absolute terms tends to increase. This suggests that while banks' technological adoption offers diversification by catering to various clients and providing different products, the use of a technological solution from the same company across multiple banks appears to have an increasing risk effect. This observation aligns with the hypothesis that there might be a correlation in the decision patterns designed by common solution providers. The reliance on similar algorithms and data sources may contribute to similarities in decision-making processes among banks, potentially amplifying the systemic risk in the banking sector.

6. Robustness Check

6.1. Alternative methods

In this Section, we aim to provide the robustness of our analyses by redefining the bank's technological measures, sample selection, and systemic risk measures. We start with the analysis of the impact of technological development on bank NPL_Ratio. However, instead of using the median number of technological solutions as a threshold to define the treated and control group, we alternatively classify banks into different groups depending on their technological intensity. Specifically, we construct a treated group consisting of banks with one and two solutions, banks with three and four solutions, and banks with five and six solutions, respectively. Again, we compare these banks to the ones without any implemented technological solutions. Our treated banks entered the treatment sample from 2011 onwards. We run the dynamic DID, as discussed in the Methodology Section. We present our results in **Figures 10 - 11**, which illustrate the coefficients for our interaction variables and the corresponding confidence intervals.

Figure 10: 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 one and two technological solutions. The control banks are all other 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.

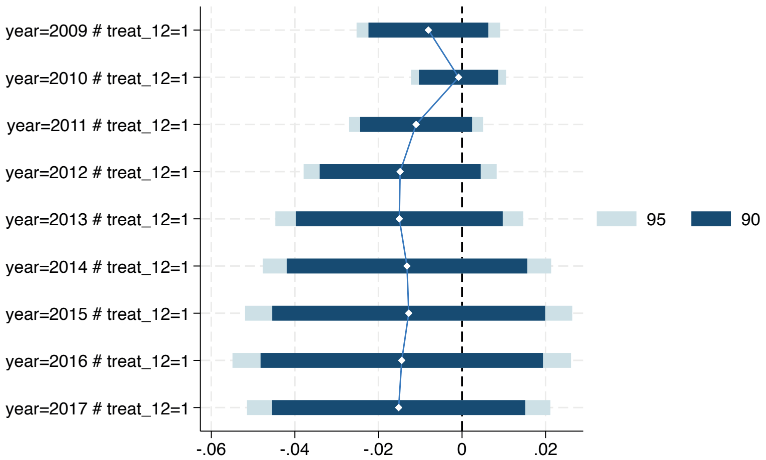


Figure 11: Role of Fintech solutions on banks' NPLs

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 all other banks. The treatment period starts in 2011.

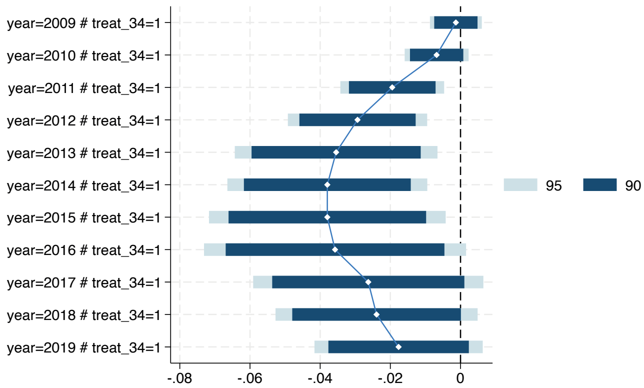
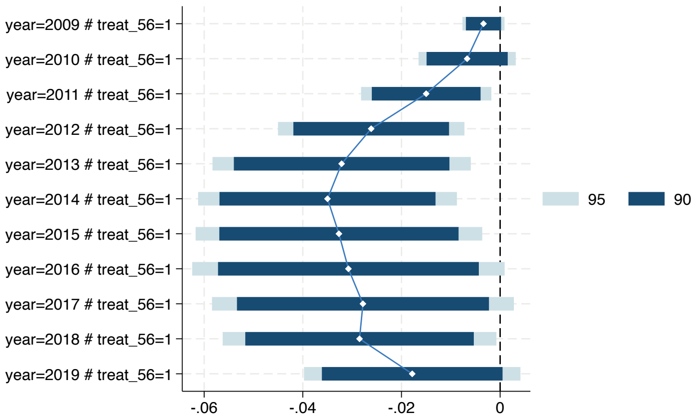


Figure 12: Role of Fintech solutions on banks' NPLs

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



Our analysis reveals heterogeneity in the effect of technological development on the level of bank NPL_Ratio depending on the number of solutions adopted, supporting our previous findings. When examining banks that adopted only one or two solutions, we observe a small decrease in non-performing loans after 2010. However, the coefficients are generally insignificant both statistically and economically. For banks that implemented three or four solutions, we note a modest decrease in NPL_Ratio between 2012 and 2016. For banks that adopted more than four but less than seven solutions, the effect is negative, statistically significant, and mostly consistent across years. It is also the most meaningful as compared to two other subsamples. These results reinforce our earlier conclusion that greater technological development leads to a decline in bank NPL_Ratio.

We also assess the robustness of our results by examining alternative measures of technological development existing in the literature. To this end, we use the share of a bank's intangible assets (Intangible_Asset) (excluding goodwill) to total bank assets as a proxy for bank digitalization. The use of intangible assets as a measure of technological development is justified because it frequently includes items of substantial value, such as patents, developed technology, and in-process research and development (Lim et al., 2020). Given that most banks in our sample have purchased technological solutions rather than developed them in-house, this variable might also reflect banks' technological development more precisely than, for example, IT spending. **Table 10** shows the regression results for the dynamic DID regressions using the *Intangible_Asset* as an alternative way of classifying banks as highly digitalized as opposed to using the number of solutions. The results are presented at the seventy-fifth quantile of this variable as a threshold to recognize banks that are truly leading in terms of digital adoption, i.e., are significantly ahead of most of their peers. At the same time, we ensure that the group of highly digitalized banks is not too small.

Table 10: Robustness Check: The impact of bank technological development on NPL_RATIO 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 HighDigital *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. 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*HighDigital	-0.00169	-0.00196	0.000843	-0.00363
	(0.00340)	(0.00345)	(0.00376)	(0.00641)
Treatment_Year2010* HighDigital	-0.00718	-0.00712	-0.00415	-0.00732
	(0.00507)	(0.00512)	(0.00535)	(0.00618)
Treatment_Year2011* HighDigital	-0.0201***	-0.0203**	-0.0176**	-0.0152**
	(0.00774)	(0.00780)	(0.00830)	(0.00669)
Treatment_Year2012* HighDigital	-0.0297***	-0.0302***	-0.0287***	-0.0307***
	(0.00911)	(0.00916)	(0.00882)	(0.0111)
Treatment_Year2013* HighDigital	-0.0324***	-0.0327**	-0.0302**	-0.0172**
	(0.0125)	(0.0125)	(0.0125)	(0.00754)
Treatment_Year2014* HighDigital	-0.0288***	-0.0293***	-0.0268**	-0.0161**
	(0.0105)	(0.0106)	(0.0101)	(0.00716)
Treatment_Year2015* HighDigital	-0.0253**	-0.0258**	-0.0238**	-0.0134*
	(0.0107)	(0.0108)	(0.0102)	(0.00680)
Treatment_Year2016* HighDigital	-0.0251**	-0.0256**	-0.0257**	-0.0186**
	(0.0109)	(0.0109)	(0.0111)	(0.00825)
Treatment_Year2017* HighDigital	-0.0194***	-0.0204***	-0.0171***	-0.0161**
	(0.00621)	(0.00657)	(0.00638)	(0.00708)
Treatment_Year2019* HighDigital	-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 FE	YES	YES	YES	YES
TIME FE		YES	YES	YES
Macro controls			YES	YES
Bank controls				YES

Our previous conclusions are further supported by the results using the alternative bank technological measures. We find that bank technological innovation has a negative effect on bank NPL_Ratio across all our specifications, and this effect becomes statistically significant after 2010. Interestingly, the effect of interaction terms before 2011 is statistically insignificant proving the assumption required by the DID regression of parallel trend in the pre-treatment period (Angrist & Pischke, 2008). Interestingly, the largest effect can be observable in 2019 when technological development has reached its peak in our sample. These results suggest that technological development seems to improve credit scoring assessment. This finding is also in line with what other researchers have found (Berg et al., 2020;Bazarbash, 2019; Berg et al., 2020; Gambacorta et al., 2020).

We also present the regression results using alternative approaches of classifying banks as technologically developed. Firstly, we allow a bank to enter the treatment group when it achieves the highest number of solutions (MAX_SOLUTION) calculated over the analyzed period. We assume that the treatment period starts in 2011. These banks are then compared to the less digitalized banks (Specification 1) as well as to banks with no technological solutions (Specification 2). The former analysis allows us to consider a greater variation between the level of technological development across the treatment and control groups. Additionally, we also present the regression results using the staggered DID when banks enter the treatment group after adoption of the first technological solution while the control group consists of banks with no technological solution. These results are presented in the Specification (3). The regression results are presented in the Appendix in **Table A2.**

The regression results confirm our previous findings providing evidence that after 2010 when the digitalization trend period spurred up, the level of NPL started to decrease at banks that decided to invest in their technological development. This is supported by the findings from Specifications (1) and (2). Interestingly, results from Specification (3) document that the TECH_DEV variable is not statistically significant suggesting that the effect of digitization does not affect a bank's risk linearly. A certain level of bank digitalization needs to be achieved to notice an effect on bank credit risk reduction. This also confirms our regression results from **Table 2** that the digitalization effect on bank NPLs is not uniformly distributed which we noticed in the Specification (1).

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 risks. 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. Using this data we test the effect of bank technological development on 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.

We present our regression results in **Table 11.**

Table 11: 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.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

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.

6.2. Endogeneity Tests

There might be concerns about some sources of endogeneity, especially, between bank NPL_Ratio and bank TECH_DEV. Firstly, bank technological development and NPLs may be simultaneously determined. Secondly, there may be a reverse causal relationship where NPLs may also influence the adoption of technological innovations in banks. Banks with higher NPLs may be more motivated to invest in technological solutions to improve their risk management and loan performance. In this case, NPLs are not solely determined by technological development but also can affect it, creating endogeneity issues. Finally, banks that choose to implement technological innovations may differ systematically from those that do not adopt such innovations, and these differences can influence the level of NPLs. Especially, one can consider that banks with a higher lending activity are more likely to implement different technologies to improve their credit risk assessment, which might also influence the level of NPLs.

In our paper, we have already addressed some sorts of endogeneity. Firstly, our DEV_TECH captures a broad scope of bank operations, both front and back-office, which are not specific to any type of bank operation. Secondly, using the probability regression we have documented that bank size and profitability are the most important determinants of bank technological adoption. Our regression results do not indicate that the NPLs level is a significant indicator of bank technological adoption which seems to suggest that NPLs do not tend to influence bank motivation for technological development.

Nevertheless, to address the above endogeneity concerns more formally, we perform the 2SLS IV regression. To this extent, we instrument bank technological variables (DEV_TECH and INTANGIBLE_ASSET) with the following variables: (i) *number of bank branches per 1000 inhabitants*, (ii) *Fintech credit in a country (mln USD)*, (iii) *number of granted patents by a bank*, and (iv) *number of patent fillings submitted by a bank*. The idea of the instruments is to proxy a bank's technological development with an effect on NPLs without being influenced by any bank specific features. While the intuition behind the granted patents and fillings patent application is straightforward, there might be a need for more explanation regarding the usage of the first two measures of bank digitalization. While the number of branches may not directly measure bank digitalization, it may still be correlated with bank digitalization efforts. Banks that actively pursue digital transformation may gradually decrease their reliance on physical branches. Concerning Fintech credit, we might expect that the digitalization of the banking sector is more advanced in regions or countries where the Fintech market is more saturated (Hryckiewicz et al., 2022; Cornelli et al., 2023). Econometrically, most our instruments have passed the validity criteria and document that they seem to be strong instruments for bank digitalization. **Table 12** presents the IV regression results for different specifications.

Table 12: Robustness Check – 2SLS Instrumental Variable Regression

The Table presents the regression results using 2SLS IV regression. TECH_DEV is defined as the number of solutions adopted by a bank (specification (1)), IT_EXPENSES measures the bank spending to operating income (Specification (2)), INTANGIBLE_ASSET is a ratio of bank intangible asset (excluding goodwill) to bank assets (Specifications (3)-(5)). TECH_DEV variables are instrumented by the following measures: (i) a number of bank branches per capita in a country, (ii) Fintech Credit (in mln) in a given country, (iii) a number of grants and fillings submitted by a bank *i* in a year *t*. Specifications (4) and (5) have been conducted on extended for the extended sample, i.e., for all banks having the SRISK measures. All regression includes the bank-and time-fixed effects. Standard errors are clustered at the bank level. Standard errors are in parentheses indicating * $p < 0.1$, ** $p < 0.05$, *** $p < 0.0$

VARIABLES	(1) **NPL_RATIO**	(2) **NPL_RATIO**	(3) **NPL_RATIO**	(4) **NPL_RATIO**	(5) **NPL_RATIO**
TECH_DEV	**TECH_DEV**	**IT_EXPENSE**	**INTANGIBLE_ASSET**	**INTANGIBLE_ASSET**	**INTANGIBLE_ASSET**
INSTRUMENT	**Bank Branch**	**Bank Branch**	**Fintech Credit**	**Number of granted patents**	**Number of grant filling applications**
TECH_DEV	-0.045***	-0.003*	-0.081**	-12.00***	-14.47***
	(0.016)	(0.002)	(0.035)	(1.308)	(3.307)
SIZE	-0.023	-0.036**	-0.039***	0.131***	0.154***
	(0.014)	(0.016)	(0.013)	(0.015)	(0.034)
EFFICIENCY	0.0002***	0.000	0.000	-0.080***	-0.102***
	(0.000)	(0.0001)	(0.000)	(0.022)	(0.038)
LOAN_ACTIVITY	0.0001	-0.002**	0.0002	0.108***	0.135***
	(0.0004)	(0.001)	(0.0003)	(0.030)	(0.048)
EQUITY_RATIO	0.001	0.002*	0.0003	0.437***	0.414***
	(0.001)	(0.001)	(0.001)	(0.063)	(0.080)
ROA	-0.004	(0.002)	-0.006***	-4.502***	-5.357***
	(0.003)	-0.006	(0.002)	(0.601)	(1.227)
GDP GROWTH	0.001	-0.002	0.0008	-0.683***	-0.736***
	(0.001)	(0.004)	(0.002)	(0.082)	(0.105)
INFLATION	-0.004	-0.015**	0.001	0.161	0.131
	(0.004)	(0.007)	(0.002)	(0.228)	(0.265)
BANK CONCENTRATION	0.002***	0.001**	-0.0001	0.0004*	0.00059*
	(0.001)	(0.001)	(0.0002)	(0.0002)	(0.0003)
Observations	476	292	280	618	618
R-squared	-0.006	0.044	0.346	-0.333	-0.876
Bank FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES
Hansen J-Statistic (exatly identified)	0.000	0.000	0.000	0.000	0.000
Cragg-Donald Wald F-statistic	18.452	12.192	14.660	14.435	12.537

The regression results provide strong evidence supporting the robustness of our findings from the DID regressions. Specifically, the coefficients of the instrumental variables used to proxy for bank technological development are consistently negative and statistically significant at the 1% level influencing bank NPLs. This indicates that greater technological innovation improves the credit risk processes, reducing the level of NPLs at banks.

Furthermore, since the Hansen J-statistic documents that our equation is exactly identified which does not allow us to perform the test of the validity of our instruments, we use the Cragg-Donald test for weak identification of instruments. Andrews et al. (2019) suggest that the "standard" rule of thumb for one instrument is that the first stage F-test should be larger than 10.[5] In our case, we notice that F-tests for all regressions are higher than 10 providing evidence that our instruments are strong. The results are also valid if we correct the test for potential biases in the coefficients and/or size of t-test, as suggested by Stock & Yogo (2005). The authors propose the corrected critical values (Stock-Yogo critical values). One rejects H_0 stating that the instruments are weak if $F>J_{10}$ (k). Again, we can do it for all our regressions. Passing these validity tests provides further confidence in the accuracy and reliability of our findings.

[5] Staiger & Stock (1997) find if first-stage F is 10 then a 2SLS 5% two-tailed t-test rejects a true null and H0: Beta=0 at a rate not "too far" from the correct 5% rate. Thus, Stock and Watson (2015) p.490 write: "One simple rule of thumb is that you do not need to worry about weak instruments if the first stage t-statistic exceeds 10".

7. Conclusion

The technological development of the financial sector has undoubtedly brought numerous benefits, but it is crucial to consider the potential risks and downsides associated with this transformation. Global organizations like the Bank for International Settlements, the Financial Stability Board, and the World Economic Forum have raised concerns about the increased risk that may arise from the ongoing digitalization process and consequent ecosystem. These concerns encompass various aspects, including limited knowledge about the types of technological solutions adopted by banks, the mechanisms driving the decisions in the banking sector, increasing reliance on external technology providers, the concentration of technology providers serving the banking sector, and as a result the intricate interdependencies within the financial system.

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 financial technology solutions of 62 major European and US banks over a period of 11 years, from 2009 to 2019. Through meticulous data collection, we obtained detailed information about the specific technological solutions implemented by these banks, their type, source of adoption, and the interlinkages between different institutions. Our analysis aims to examine the effects of bank technological development on bank non-performing loans and systemic risk measures within the banking sector. To achieve this, we employ various econometric techniques such as static and dynamic DID models, synchronicity analysis, and two-way fixed-effects linear regressions.

The findings of our study reveal several important insights. Firstly, we observe that banks with a higher degree of technological development tend to exhibit lower levels of non-performing loans. Moreover, this effect becomes more pronounced as digitalization progresses over time and as banks adopt a greater number of technological solutions. 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 technologically innovative 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. 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 management strategies. A greater product range approaching a more diverse group of customers seems to create a diversification effect in the system.

Conversely, we find that the concentration of technology providers to banks notably enhances 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 providers seems to increase risk through more correlated decision patterns utilized by the same technology 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, suggesting that digitalized banks are more prone to bank runs because of a 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 monitor the nature of technologies provided to different institutions by external providers.

Appendix

Table A1: Variable definitions

Variable	Definition
A. Bank-level variables	
SIZE	Natural logarithm of assets (in millions) in constant prices
CREDTI_ACTIVITY	Ratio of net loans to total assets
TIER1_RATIO	Tier1 capital to risk-weighted asset
NONINTEREST _ACTIVITY	Non-interest income to bank 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
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%).
Lrmes	The Long-Run Marginal Expected Shortfall.
Beta	The co-movement bank returns with market returns.
CORR	The co-movement bank returns with market returns.
VOL	Stock volatility.
LEV	A bank’s leverage.
B. Digitalization variables	
AUTOMATIZATION	Binary variable identifying situations in which a firm's main bank used technological solutions classified as *Automation software* in a given year
BLOCKCHAIN	Binary variable identifying situations in which a firm's main bank used technological solutions classified as *Blockchain* in a given year
ANALYTICS	Binary variable identifying situations in which a firm's main bank used technological solutions classified as *Data analytics* in a given year
ONLIN_LENDING	Binary variable identifying situations in which a firm's main bank used technological *Solutions for lending* in a given year
MOBILE_PAYMENT	Binary variable identifying situations in which a firm's main bank used technological *Solutions for payments* in a given year
PERSONAL_FIN	Binary variable identifying situations in which a firm's main bank used technological *Solutions for personal finance* in a given year
REG_TECH	Binary variable identifying situations in which a firm's main bank used technological solutions classified as *Regulatory technology* in a given year
TECH_DEV	The index of overall innovativeness of a bank, i.e., the sum of AUT.SOFT, BLOCKCHAIN, ANALYTICS, LENDING, PAYMENTS, PERSON.FIN, AND REGULAT
TECH_SHARING	Number of banks’ sharing the same technology provider with a bank *i* at time *t*
C. Macro variables	
GDP growth	Growth of a country’s GDP
Inflation	Consumer price index (%)
Bank Concentration	Asset concentratio of the largest 5 banks in a country

Table A2: Alternative definition of treatment and control groups

The regressions present the results for DID estimations using the alternative definitions of the treatment and control groups. In the first specification (1) we define treated banks as those with the highest number of solutions after 2010 whereas this number is defined as the maximum number of technological solutions over the whole sample period in a bank (MAX_SOLUTION). The control group consists of banks which do not enter the treatment group after 2010. In Specification (2) we define the treated banks as those that have adopted any technological solution after 2010 while the control group consists of banks with no solutions. Specification (3) presents the regression results using the staggered DID when we allow control and treat bank groups to change across time. Banks that have adopted any solution enter our treatment group in a year when the adoption has happened; otherwise, they enter the control group. Treatment_Years is a dummy equaling one for the years after 2010; for the years preceding 2011 it takes a value of zero.

VARIABLES	(1) **NPL_RATIO**	(2) **NPL_RATIO**	(3) **NPL_RATIO**
MAX_SOLUTION* Treatment_Years	-0.00313**	-0.0197**	
	(0.00123)	(0.00893)	
TECH_DEV*YEAR_DUMMY			0.00651
			(0.00498)
L1.SIZE	-0.0224**	-0.0427**	-0.0409**
	(0.00979)	(0.0163)	(0.0170)
L1.PROFITABILITY	-0.00655**	-0.00486*	-0.00536*
	(0.00256)	(0.00283)	(0.00280)
L1.EFFICIENCY	9.33e-05	0.000152**	0.000143**
	(6.49e-05)	(6.53e-05)	(6.84e-05)
L1.LOAN ACTIVITY	-0.000586	-0.00194*	-0.00190*
	(0.000527)	(0.00107)	(0.00109)
L1.TIER1_RATIO	0.00179	0.00134	0.00174
	(0.00166)	(0.00145)	(0.00150)
L1.LIQUIDITY		-0.0790	-0.0770
		(0.0495)	(0.0517)
GDP GROWTH	0.00228	0.00223	0.00228
	(0.00163)	(0.00159)	(0.00154)
INFLATION	-0.00490	-0.00529	-0.00567
	(0.00563)	(0.00529)	(0.00552)
BANK CONCENTRATION	0.00117	0.000960	0.000942
	(0.000705)	(0.000576)	(0.000584)
Constant	0.404**	0.947**	0.905**
	(0.182)	(0.378)	(0.394)
Observations	445	445	445
R-squared	0.235	0.286	0.275
Time FE	YES	YES	YES
Bank FE	YES	YES	YES

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