Anchoring Stability: Fin tech's Revolution in Modern Banking

https://www.doi.org/10.63355/A7743JA8

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Abstract:

Amid the rapid digital transformation of the financial sector, technological advancements are reshaping traditional banking practices. This study investigates the relationship between Fin tech credit and bank stability, proxied by Credit Risk Distance (CRD), within the global banking sector. Specifically, we examine whether Fin tech credit increases competitive pressures and financial risk, or whether traditional banks are effectively adapting to these digital disruptions. Using panel data estimation techniques with firm and country-year fixed effects, our results show that increased Fin tech credit is associated with higher CRD, indicating a lower likelihood of default and a potential stabilizing effect on bank risk. Sub-sample analyses further compare distressed versus non-distressed banks, as well as highly leveraged versus less-leveraged institutions. Robustness of the findings is confirmed using the System Generalized Method of Moments (System-GMM). These findings contribute to the emerging literature on Fin tech and financial stability and offer practical implications for policymakers, bank executives, and investors navigating the evolving digital financial landscape.

Keywords:

Fin tech credit; Credit risk distance; Fin tech Adoption; Banking Stability; Global Banks.

1. Introduction :

The seismic shift caused by Financial Technology (Fin tech) disruption in the global banking sector has sparked considerable debate and scholarly inquiry into its implications for financial stability. The advent of Fin tech has been characterized by its rapid assimilation of digital technologies to enhance or innovate financial services, disrupting the conventional operations of the banking industry (Haddad & Hornuf, 2023). The proliferation of digital lending platforms, peer-to-peer payment systems, and blockchain-based transactions have redefined consumer expectations and the operational models of traditional banks (Frost et al., 2019; Thakor, 2020). While these innovations offer the promise of increased efficiency and accessibility in financial services, they also introduce new risks and competitive pressures that could potentially destabilize established banking institutions. One of the critical challenges in assessing the impact of Fin tech on banking stability is the dynamic and multifaceted nature of Fin tech itself. Fin tech firms operate across a broad spectrum of financial activities, from lending and payments to wealth management and insurance, often leveraging cutting-edge technologies like artificial intelligence, big data analytics, and blockchain (Philippon, 2016). This diversity complicates the task of identifying and quantifying the specific effects of Fin tech disruption on traditional banking metrics, including the CRD, which has been a reliable indicator of a bank's financial health and its proximity to default.

The confluence of financial technology and banking has ushered in a new era of possibilities where Fin tech credit represents a transformative shift in the financial services sector (Balyuk, 2023), leveraging cutting-edge technology to redefine traditional lending practices. At its core, Fin tech credit employs APIs, big data, artificial intelligence, and secure connections to banking data to expedite and enhance the decision-making process for lenders (Murinde et al., 2022; Balyuk et al., 2022). This approach not only accelerates the loan application process but also broadens the spectrum of data utilized for assessing borrowers' creditworthiness, moving beyond traditional metrics like credit scores and employment history. Fin tech platforms enable diverse lending models, including peer-to-peer lending, mortgages, business loans, and investor loans, offering a more inclusive, efficient, and accessible financial ecosystem for both borrowers and lenders[1].

(1) **Please see**: https://plaid.com/resources/Fin tech/what-is-Fin tech-lending/

The rise of Fin tech credit has been paralleled by a significant global growth trajectory for the Fin tech sector at large (Gopal & Schnabl, 2022). This sector, which currently commands a mere 2% of global financial services revenue, is projected to swell to $1.5 trillion by 2030(2), potentially accounting for nearly a quarter of all banking valuations. This shift underscores the vital role of Fin tech in fostering financial inclusion, especially in emerging markets where traditional banking infrastructures are less established. Furthermore, the evolving landscape underscores a pivotal transition from payments to B2B (business-to-business) and B2B2X (business-to-business-to-any user) services as the leading edge of Fin tech growth signalling an expanding horizon for Fin tech solutions (Jakšič & Marinč, 2019). Meanwhile, regulatory frameworks and partnerships between traditional financial institutions and Fin tech companies are evolving to support this growth, ensuring that innovations continue to flourish while maintaining system stability and consumer protection.

A notable shift occurred in the U.S. personal loan market, where Fin tech companies significantly increased their market share at the expense of traditional banks and credit unions. In 2013, Fin tech companies accounted for only 5% of the U.S. personal loan market. By 2018, their share had surged to 38%, surpassing banks, which saw their share drop from 40% to 28% over the same period. Credit unions also experienced a decline, with their share falling 10 percentage points to 21%(3). Regulation plays a dual role here; while it aims to protect the banking system and ensure financial stability, it also inadvertently advantages Fin tech firms by allowing them to operate with lower costs due to the absence of stringent capital requirements and other regulatory burdens that banks face. This regulatory landscape creates an uneven playing field, favoring Fin tech firms in competition against traditional banks(4). On the flip side, in 2023, Statista highlighted that Fin tech ventures globally attracted $105 billion in investments, reflecting the sector's explosive expansion. Gartner's forecasts suggest that by 2025, four out of every five traditional banking institutions will either form alliances with or purchase Fin tech companies to boost their digital prowess. A significant uptick of 40% in online searches for digital banking ecosystems over the last year has been documented by SEMrush, un-

(2) **Please see**: https://www.bcg.com/press/3may2023-Fin tech-1-5-trillion-industry-by-2030

(3) **Please see**: https://www.stlouisfed.org/on-the-economy/2021/april/banks-challenges-Fin tech-disruption

(4) **Please see:** https://corpgov.law.harvard.edu/2019/11/20/Fin tech-bigtech-and-the-future-of-banks/

derscoring a spike in public interest. The burgeoning collaboration between established banks and Fin tech entities is fast-tracking the delivery of superior digital services and customer experiences[(5)].

Traditional banking services have been revolutionized by digital platforms, data analytics, and innovative financial products (Hu et al., 2022). As customers demand seamless experiences and real-time services, banks are compelled to harness the potential of Fin tech to not only remain competitive but also to enhance their risk management capabilities. Against this backdrop, the Credit risk distance emerges as a critical measure that reflects a bank's ability to weather financial storms and economic downturns, thus directly influencing investor confidence, regulatory scrutiny, and overall systemic stability (Nagel & Puranandam, 2020). Fin tech lenders, by offering quicker, more accessible loans to consumers and businesses, directly compete with traditional banks, potentially leading to a decline in banks' profitability and weakening their financial position (Fung et al., 2020), which could decrease their CRD. Furthermore, the operational efficiency and lower cost structures of Fin tech platforms allow them to offer loans at competitive rates, pressuring banks to reduce their interest rates to remain competitive by squeezing the profit margins of banks, impacting their earnings and capital adequacy, and adversely affecting their CRD by diminishing the buffer against unexpected losses (Boot et al., 2021).

Another challenge is the advanced data analytics and non-traditional data used by Fin tech lenders for credit assessments, which could identify creditworthy borrowers overlooked by banks' conservative credit models where this innovation can pressure banks to adapt their risk management practices, potentially introducing vulnerabilities during the transition period that could negatively influence their CRD. Conspicuously, regulatory arbitrage also plays a role, as Fin tech companies often operate under different regulatory frameworks than banks (Buchak et al., 2018), leading to regulatory disparities that could stress banks to engage in riskier lending practices themselves to remain competitive, potentially destabilizing their financial health and CRD. To compete with Fin techs, banks are required to make substantial investments in digital technologies, cybersecurity, and data analytics. These investments introduce operational risks and can

(5) **Please see:** https://blog.emb.global/Fin tech-vs-traditional-banking/

strain resources, impacting banks' financial stability and CRD. Additionally, as consumer expectations shift in favor of digital experiences provided by Fin tech credit platforms, banks may struggle to retain customers, leading to reduced deposit inflows and lending opportunities, further challenging their financial stability and CRD.

The literature on the impact of Fin tech on banking stability, while growing, remains nascent, with empirical studies often yielding mixed results. Research has primarily focused on individual aspects of Fin tech's impact, such as the effect on lending practices, payment systems, or regulatory challenges, without fully integrating these dimensions into a comprehensive assessment of banking stability (Jagtiani & Lemieux, 2018; Cornelli et al., 2020). Meanwhile, banks are anticipated to formulate strategic responses to counteract the threats posed by Fin tech disruptions, a noticeable gap persists in scholarly exploration concerning the repercussions of these strategies on banks' CRD. Furthermore, the existing literature on Fin tech credit appears fragmented (Cai, 2018), marked by a blend of conflicting and inconclusive findings (Singh et al., 2021).

Based on these apprehensions, we contribute to the existing field of knowledge in several ways. First, to the authors' best knowledge, this is the first study to investigate the relationship between Fin tech credit and Credit risk distance of global banks for the year encompassing 2013 to 2020. The data has been sourced for global banks based on the database provided by Cornelli et al., (2020) on Fin tech credit. The study potentially highlights the adaptive strategies employed by global banks in response to Fin tech competition. As Fin tech firms target niche markets and underserved segments, traditional banks may have adjusted their business models, embracing technological innovation and forming strategic partnerships with Fin tech companies to enhance their own digital offerings. These adaptations could have implications for banks' risk management practices and their CRD. Second, we worked on the data of global banks containing 35 countries as provided by Cornelli et al., (2020) for 685 banks for the period encompassing 2013 to 2019 constituting 4505 bank-year observations. The rationale for selecting this timeframe is that significant technological advancements in Fin tech have been experienced, including the use of artificial intelligence and machine learning for credit risk assessment, blockchain for transaction security, and big data analytics for personalized financial services. Thus, these technologies have potentially altered the risk profiles of loans offered by Fin tech platforms, affecting the competitive environment for global banks and, consequently, their CRD metrics.

Third, methodologically, we employed robust fixed effects methods on the dataset with and without controls. In addition, we adopted the Altman (1968) approach as a measure of credit risk distance (CRD) rather than relying on Merton's (1974) model as Altman's method, fundamentally an empirical bankruptcy prediction model, uses a company's financial ratios to determine its financial health and predict its potential failure. This approach is more appropriate for our analysis because it provides a direct, quantitative assessment of a firm's risk of default based on its financial statements. Unlike Merton's model, which conceptualizes a firm's equity as a call option on its assets and requires the market value of assets and their volatility. Contrarily, Merton's model, rooted in option pricing theory, offers a sophisticated approach to estimating a bank's default probability based on market data. However, it assumes market efficiency and transparency, which might not always capture the actual realities of default faced by banks today. Accordingly, we conducted sub-sample analysis for distressed banks, high versus low leveraged banks, and small versus large-sized banks to indicate varying impacts of the given relationship for multiple sub-samples. Finally, we conducted the robustness analysis and tested for potential endogeneity and unobserved heterogeneity in our model to provide validated results.

The findings of our analysis demonstrate that Fin tech credit exerts a significant influence on Credit Risk Distance (CRD) across banks globally, both in baseline models and those with additional controls, using robust fixed effects estimation. Specifically, increased Fin tech credit activity is associated with a lower likelihood of bank default, suggesting that Fin tech may play a stabilizing role in the evolving financial landscape. As Fin tech continues to expand, its impact on the risk profile of traditional banking institutions becomes more pronounced, underscoring the need for adaptive strategies that align with emerging technological and competitive dynamics. These results carry important implications for policymakers, financial institutions, and academic researchers seeking to better understand the risk implications of financial innovation.

The rest of the study is organized as follows: Section 2 provides review of earlier literature and hypotheses development. Section 3 highlights methodology, data, and variables. Section 4 gives empirical results and discussion. Section 5 concludes the study along with implications, future research directions, and limitations.

2. Literature Review:

While there are arguments both in favor of and against the correlation between Fin tech credit and CRD, a closer examination suggests that the relationship is multifaceted, context-dependent, and influenced by various market dynamics. Proponents of the link between Fin tech credit and CRD argue that these technologies have the potential to enhance credit assessment accuracy (Duan, 2021). By offering vast amounts of alternative data and leveraging machine learning algorithms, Fin tech platforms provide a more comprehensive view of borrower creditworthiness (Kayode, 2023). This, in turn, could lead to a finer segmentation of borrowers according to their risk profiles, thereby reducing information asymmetry and improving the precision of CRD calculations. Consequently, this argument asserts that Fin tech credit could positively impact CRD by refining risk estimation and enabling lenders to allocate capital more efficiently.

On theoretical grounds, Peer-to-Peer (P2P) lending theory introduces another layer of complexity to the relationship between Fin tech credit and Credit Risk Distance (CRD). P2P lending platforms, often facilitated by Fin tech innovations, enable direct borrowing and lending between individuals or small businesses without traditional financial intermediaries. Proponents of P2P lending suggest that its decentralized nature could enhance the accuracy of credit risk assessment (Duan, 2021). One argument in favor of P2P lending's impact on CRD centers around the notion of information aggregation (Kavassalis et al., 2018). P2P platforms allow lenders to access a broader range of borrower information than traditional banks, potentially leading to a more comprehensive assessment of credit risk. Meanwhile, the absence of stringent regulatory oversight in some P2P lending markets might lead to a higher degree of information asymmetry compared to traditional lending, potentially undermining the accuracy of CRD calculations.

From a systemic perspective, the growth of Fin tech credit could introduce new dimensions of interconnectedness and risk contagion (Li et al., 2020). The decentralized nature of Fin tech credit might result in dispersed pockets of default risk that could potentially spread through interconnected borrowing and lending relationships. This, in turn, might complicate the estimation of CRD for individual borrowers as systemic risks become entwined with borrower-specific risk profiles. Thus, P2P lending theory adds both opportunities and challenges to the relationship between Fin tech credit and Credit Risk Distance. While the decentralized nature of P2P lending platforms could potentially enhance information aggregation and credit risk assessment, concerns related to information quality, regulatory oversight, social bias, and systemic risks need to be carefully considered.

P2P lending, as rooted in economic theory, operates on the principle of disintermediation (Gu, 2024), wherein individual lenders directly engage with individual borrowers through online platforms, circumventing traditional financial intermediaries. From an economic standpoint, P2P lending challenges the traditional supply and demand dynamics of credit markets by altering information asymmetry, transaction costs, and risk-sharing mechanisms (Li et al., 2020). Proponents argue that this disruption could impact CRD calculations by reshaping credit risk assessment and risk distribution. The theory suggests that P2P lending, by leveraging technology to aggregate diverse and granular borrower information, can enhance the efficiency of credit allocation resulting in a more accurate representation of credit risk, subsequently influencing the CRD metric. By connecting lenders directly with borrowers and bypassing intermediaries, P2P lending platforms have the potential to reduce information asymmetry (Buchak et al., 2018), thereby enabling lenders to make more informed lending decisions.

However, a comprehensive critique demands consideration of the economic challenges inherent in P2P lending theory. While disintermediation has the potential to mitigate some information asymmetry (Gu, 2024), it also introduces new dimensions of risk, particularly related to moral hazard and adverse selection. Without the oversight and risk-sharing mechanisms of traditional intermediaries, lenders might face higher default risks and reduced avenues for recourse. Additionally, the decentralized nature of P2P lending could result in a fragmented market with varying lending standards, potentially leading to inconsistent CRD assessments across different platforms. Furthermore, the economic theory of P2P lending highlights the influence of regulatory and institutional factors. The degree of regulatory oversight varies across jurisdictions and impacts the operational and risk management practices of P2P lending platforms (Wei & Lin, 2017). Regulatory interventions aiming to safeguard market integrity and protect investor interests could influence the functioning of P2P lending and, by extension, its impact on CRD calculations.

To reconcile traditional theory with our findings, it is essential to engage with emerging literature that highlights how Fin tech can enhance risk management and institutional adaptation. Economic theories generally suggest that competition from Fin tech firms should lead traditional banks to either take on riskier loans to maintain market share (Vives, 2017; Thakor, 2020) or invest in operational innovations that improve risk management and reduce exposure (Navaretti et al., 2018; Frost, 2020). Our findings, which indicate a positive relationship between Fin tech activity and CRD, appear to align more closely with the latter channel. This may suggest that incumbent banks have adapted to the competitive threat by strengthening their internal credit assessment capabilities, improving operational resilience, and selectively collaborating with Fin tech partners.

Additionally, the theory of regulatory arbitrage adds further evidence. Fin tech firms often operate in less regulated environments, allowing them to offer services more efficiently (Buchak et al., 2018). This cost advantage may pressure incumbent banks to either advocate for regulatory reforms or adopt similar technological efficiencies. While this could lead to short-term misalignments in oversight, it may also encourage strategic realignment that results in improved risk profiles among regulated institutions.

In line with broader developments in the literature, various metrics have been proposed for measuring bank risk, each offering distinct advantages and limitations. One widely used alternative to the Altman Z-score is the bank Z-score, defined as the sum of ROA and the equity-to-assets ratio, divided by the standard deviation of ROA (Chiaramonte et al., 2016; Laeven and Levine, 2009). Although this measure offers strong theoretical alignment with banking sector dynamics, its calculation was not feasible in this study due to the unavailability of consistent ROA volatility data across time and institutions.

Another commonly cited proxy is the ratio of risk-weighted assets to total assets, which reflects banks' exposure-adjusted lending risk (Logan, 2001; Berger and Bouwman, 2013; Berger et al., 2016). However, the completeness and comparability of this variable were limited in our cross-country dataset.

Additionally, market-based indicators such as equity volatility and earnings volatility (Saunders et al., 1990; Esty, 1998; Laeven and Levine, 2009) have been employed to capture investor-perceived and performance-based risk. These measures, while analytically rich, were not suitable for the scope of this study due to incomplete coverage for non-listed banks.

Taken together, the methodological literature underscores the complexity of risk estimation and the need to select appropriate proxies based on the context, data availability, and institutional characteristics. The Altman Z-score, although originally designed for industrial firms, has been validated in several financial studies (e.g., Gutiérrez-López et al., 2022) and provides a consistent, interpretable risk measure across the full sample.

In this way, although traditional theoretical channels raise concerns about Fin tech- induced instability, the evidence in our study points to an evolving dynamic. Rather than exacerbating risk, the growth of Fin tech credit appears to be contributing to bank stability. This underscores the importance of analyzing Fin tech's impact not as a static threat, but as a catalyst that compels legacy institutions to adapt, innovate, and potentially strengthen their risk management frameworks.

3.. Data and methodology :

3.1. Sample selection :

Our sample covers the data of 685 global banks from 35 countries for the period 2013-2019. The data for the study was obtained from different sources: The CRD and controls were obtained from the Refinitiv Eikon Database and S&P Global Market Intelligence. The three Fin tech credit measures were obtained from Cornelli et al. (2020). Our sample includes banks and consumer lending firms, excluding the non-financial firms. The final sample comprises a panel of 4505 bank-year observations. The distribution of the data for the sample firms are presented in Table 2. The main variable of interest is Fin tech credit. We also employ the two alternative measures of Fin tech credit i.e., Fin tech per capita and Fin tech as a ratio of GDP. The main dependent variable is the Credit risk distance using the Altman ZScore (Gutiérrez-López et al., 2022). The definitions of all variables are provided in Table 1.

Table 1: Description of Variables

Variables	Measurement	Source
Credit risk distance	Natural log of Altman's Z-score is computed as 3.3*(earnings before interest and taxes/total assets) + 1.2*(working capital/total assets) + sales/total assets) + 0.4* (market value equity/book value of total liabilities) + 1.4*(retained earnings/total assets)	**Altman (1968)**
Fin tech credit	The amount of Fin tech credits	**Cornelli et al. (2020)**
Fin tech per capita	Total Fin tech Credit divided by total population.	**Cornelli et al. (2020)**
Fin tech/GDP	Total Fin tech Credit divided by gross domestic products.	**Cornelli et al. (2020)**
Leverage	The ratio of total liabilities to total asset.	
Firm Size	The natural logarithm of total assets.	
Profitability	The ratio of earnings before interest and taxes to total assets.	
Working Capital	The difference between current assets and current liabilities.	
Sales Variation	Variation of the ratio of sales to total assets compared to the previous year.	
Loan Loss Provisions	It is calculated by dividing loan losses by the total loan.	
Non-performing Loans	It is calculated as the sum of subprime, dubious, and loss loans to various loans.	

3.2. Methodology:

To examine the impact of Fin tech credit on Credit risk distance, this study employs the following model specification in general terms.

$$〚CreditRiskDistance〛\_(i,t)=\gamma\_0+ 〚\gamma\_1 \text{ Fin tech Credit}〛\_(i,t)+ 〚Controls〛\_(i,t)+ \eta\_t+ \nu\_(i,t) \quad ... (1)$$

where, is the intercept, and is the error term and i and t represent firm and year, respectively. Control variables include leverage, firm size, probability, working capital, sales variation, loan loss provisions, and non-performing loans. First, we employed baseline regression followed by alternative measures of Fin tech with and without controls. Then, we employed sub-sample analysis where we compared distressed banks with high-leveraged and low leveraged banks and large sized versus small-sized banks.

While several additional bank-level and macroeconomic control variables (e.g., revenue diversification, operational efficiency, loan growth, capital adequacy, and market concentration) have been proposed in the literature as potential determinants of credit risk, this study focuses on a parsimonious model specification to maintain comparability across countries and institutions. To account for unobserved heterogeneity and omitted macro-institutional effects, we employ firm fixed effects and country-year fixed effects, which absorb time-invariant characteristics of banks as well as time-varying country-level dynamics. This approach ensures model robustness while allowing for generalized inference across a diverse international sample.

3.3. Descriptive statistics :

The results of the summary statistics are presented in Table 2. The Credit risk distance (CRD) values, with both mean and median in the negative figures, signal an overarching risk of default across the entities under study reflecting a general trend towards financial distress, albeit with a relatively concentrated distribution suggesting a commonality of default risk. The range from -0.900 to 0.680 in CRD underscores the variance in financial health, indicating that while some banks are on firmer ground, others are near or at risk of default. Fin tech credit's high mean and closely aligned median suggest a robust engagement with Fin tech services across the sample, with a slightly left-skewed distribution hinting at outliers with particularly high lending volumes. Nonetheless, the compact standard deviation points to a widespread, consistent Fin tech credit activity, highlighting the sector's significant penetration. The Fin tech per capita data, with its large standard deviation relative to the mean, reveals a broad disparity in Fin tech credit's impact across different regions or populations. This wide variance, coupled with the extensive range between the minimum and maximum values, illustrates the unequal distribution and accessibility of Fin tech services. Conversely, the Fin tech/GDP ratio, characterized by minimal mean and median values and a narrow standard deviation, suggests that despite Fin tech's rapid expansion, its scale relative to the overall economic output remains limited. This indicates that Fin tech's impact, while transformative within the financial services sector, constitutes a small fraction of total economic activity.

The Leverage statistics indicate a high level of financial leverage across the entities, with minimal variability suggesting a common strategy of employing debt to drive growth, albeit with the associated risk of increased financial vulnerability. Diversity in Firm Size across the global banks reflects the financial ecosystem's varied nature, with both small and large banks represented. This suggests a broad spectrum of entities engaged in both Fin tech and traditional banking activities, encompassing a range of bank sizes. The Profitability metrics, with low, tight-knit values, imply modest but consistent profitability across the banks pointing to a competitive environment where profit margins are maintained at a modest level, potentially due to market pressures or the inherent risks of the financial sector. Working Capital and Sales Variation figures shed light on operational dynamics. Negative average working capital suggests potential liquidity challenges, while negligible sales variation indicates stable revenue streams, albeit without significant growth. Lastly, Loan Loss Provisions and Non-performing Loans provide insights into credit risk management, with variability in these metrics reflecting different approaches and success rates in managing loan portfolios and credit risk among the banks.

The results of the correlation matrix are presented in Table 3. The correlation coefficients between the variables are less than 0.800 expect for the correlation coefficients between the alternative Fin tech credit measures (Fin tech credit, Fin tech per capita, Fin tech/GDP). Thus, there are no multicollinearity issues between the independent variables as reported in Table 3.

Table 2: Descriptive statistics

Variables	Mean	Median	.Std. Dev	Minimum	Maximum
Credit risk distance	-0.596	-0.666	0.241	-0.900	0.680
Fin tech credit	23.969	24.250	0.954	22.058	24.972
Fin tech per capita		107.250	66.580	11.860	213.75
Fin tech/GDP	0.002	0.002	0.001	0.000	0.003
Leverage	0.888	0.891	0.022	0.761	0.967
Firm Size	9.058	8.819	1.587	6.961	11.929
Profitability	0.015	0.015	0.004	0.000	0.040
Working Capital	-0.870	-0.782	1.032	-7.254	2.823
Sales Variation	0.000	0.000	0.005	-0.054	0.024
Loan Loss Provisions	-6.353	-6.253	1.006	-11.513	-3.214
Non-performing Loans	0.208	0.300	0.410	-3.219	1.475

Table 3: Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Credit risk distance	1.000										
(2) Fin tech credit	-0.017	1.000									
	(0.639)										
(3) Fin tech per capital	-0.010	0.932*	1.000								
	(0.773)	(0.000)									
(4) Fin tech/GDP	-0.012	0.954*	0.997*	1.000							
	(0.738)	(0.000)	(0.000)								
(5) Leverage	-0.024	-0.062*	-0.090*	-0.084*	1.000						
	(0.493)	(0.075)	(0.010)	(0.016)							
(6) Firm Size	0.495*	0.090*	0.096*	0.095*	-0.129*	1.000					
	(0.000)	(0.010)	(0.006)	(0.006)	(0.000)						
(7) Profitability	0.245*	0.072*	0.107*	0.101*	-0.173*	0.073*	1.000				
	(0.000)	(0.038)	(0.002)	(0.004)	(0.000)	(0.036)					
(8) Working Capital	0.028	-0.021	-0.024	-0.023	0.019	-0.220*	0.041	1.000			
	(0.421)	(0.551)	(0.497)	(0.506)	(0.585)	(0.000)	(0.240)				
(9) Sales Variation	0.006	0.009	0.031	0.030	0.004	0.000	0.153*	0.053	1.000		
	(0.863)	(0.806)	(0.374)	(0.397)	(0.903)	(0.991)	(0.000)	(0.127)			
(10) Loan Loss Provisions	*0.293	*-0.100	*-0.110	*-0.107	*0.091	*0.273	*-0.079	*-0.098	0.041	1.000	
	(0.000)	(0.007)	(0.003)	(0.004)	(0.013)	(0.000)	(0.031)	(0.008)	(0.264)		
(11) Non-performing Loans	*0.147	-0.036	-0.028	-0.029	*0.103	*-0.073	*-0.121	-0.033	0.032	-0.048	1.000
	(0.000)	(0.309)	(0.429)	(0.412)	(0.003)	(0.039)	(0.001)	(0.350)	(0.369)	(0.196)	

*p<0.01, ** p<0.05, * p<0.1 ****

4. Empirical Results and Discussion:

4.1. Baseline Results:

Table 4 presents the relationship between Fin tech credit and the Credit risk distance (CRD) of financial institutions, using two different robust fixed effect models – one without controls (Model 1) and the other with controls (Model 2). The inclusion of controls in Model 2 showcase how various factors beyond Fin tech credit impact CRD. Model 1 highlights a positive and statistically significant relationship between Fin tech credit and CRD, with a coefficient of 0.0329, indicating that an increase in Fin tech credit is associated with an increase in the CRD, suggesting a reduction in default risk aligning with the perspective that Fin tech credit, by providing alternative financing options, can enhance the financial stability of borrowers (Philippon, 2016).

Model 2, incorporating controls such as leverage, firm size, profitability, working capital, sales variation, loan loss provisions, and non-performing loans, further refines this relationship. Notably, the coefficient for Fin tech credit increases to 0.0451, reinforcing the notion that Fin tech credit positively impacts financial stability, even when accounting for other influential factors. This could be attributed to Fin tech's role in improving access to capital and enhancing risk assessment capabilities (Boot et al., 2021). Leverage is negatively associated with CRD, as shown by a coefficient of -1.4249, indicating that higher leverage corresponds to a higher default risk consistent with traditional financial theory, which posits that higher debt levels can increase the financial fragility of institutions (Modigliani & Miller, 1958). The negative coefficient for firm size (-0.0443) suggests that larger firms have a slightly higher risk of default, possibly due to their complexity and the challenges in managing large-scale operations efficiently (Rajan & Zingales, 1998).

Interestingly, profitability is not significantly related to CRD in this model, indicating that short-term profits may not directly influence a firm's long-term default risk. However, working capital and sales variation, with coefficients of 0.1249 and 0.5528 respectively, highlight the importance of operational efficiency and revenue stability in mitigating default risk. Loan loss provisions and non-performing loans, with coefficients of 0.0093 and -0.0204 respectively, underscore the critical role of sound credit risk management practices in enhancing financial stability. Adequate provisioning for loan losses and minimizing non-performing loans are essential for maintaining a healthy distance from default. The constant term in Model 1 indicates the baseline level of CRD in the absence of the specified variables, while its significance diminishes in Model 2, suggesting that control variables included in the study account for a substantial portion of the variation in CRD. The increase in R-squared from Model 1 to Model 2 indicates that the inclusion of control variables provides a more comprehensive explanation of the factors influencing CRD.

Intuitively, the positive association between Fin tech credit and the Credit risk distance (CRD) underscores the potential stabilizing effect of Fin tech on the financial sector aligning with the argument that Fin tech firms, through innovative lending practices, could enhance financial accessibility and efficiency, thereby reducing the likelihood of default among borrowers (Philippon, 2016). The inclusion of Fin tech services in the financial landscape introduces a diversification of credit sources and risk assessment technologies, potentially mitigating the risk profile of borrowers and the sector at large. The significant negative coefficient for leverage within the controlled model echoes the foundational principles of financial management, where higher leverage is associated with higher default risk (Modigliani & Miller, 1958). This finding suggests that despite the growth in alternative lending forms, traditional metrics of financial health, such as leverage ratios, remain pivotal in determining the stability of financial institutions. The heightened risk associated with increased leverage highlights the need for stringent debt management practices, especially in an era where the proliferation of lending platforms amplifies the availability of credit.

The counterintuitive finding regarding firm size, indicating a slight increase in default risk for larger firms, might reflect the complexities and bureaucratic inefficiencies that can plague large organizations (Rajan & Zingales, 1998). Larger firms, despite their resources, may face agility challenges in responding to financial stress or operationalizing innovation, unlike smaller, more nimble firms that can quickly adapt to changes in the financial environment. Contrary to expectations, profitability's non-significant impact on CRD suggests that short-term financial performance may not directly correlate with long-term stability, pointing towards the importance of strategic management decisions beyond mere profit maximization. This highlights the multifaceted nature of financial health, where operational efficiency, captured through working capital and sales variation, plays a critical role in safeguarding against default (Deloof, 2003). Lastly, the role of loan loss provisions and non-performing loans emphasizes the critical importance of credit risk management. Adequate provisioning acts as a buffer against potential losses, while effective management of non-performing loans is essential for maintaining a healthy portfolio, thus contributing to the overall stability of financial institutions (Berger & DeYoung, 1997).

Table 4: Relationship between Fin tech credit and Credit risk distance

Dep. Var.: Credit risk distance	Robust Fixed Effect Model (Without Controls)	Robust Fixed Effect Model (With Controls)
	(1)	(2)
Fin tech credit	0.0329***	0.0451***
	(0.0001)	(0.0000)
Leverage		-1.4249***
		(0.0000)
Firm Size		-0.0443***
		(0.0080)
Profitability		1.6001
		(0.2438)
Working Capital		0.1249**
		(0.0453)
Sales Variation		0.5528*
		(0.0976)
Loan Loss Provisions		0.0093***
		(0.0010)
Non-performing Loans		-0.0204***
		(0.0067)
Constant	-1.4065***	0.0979
	(0.0000)	(0.7735)
Observations	4505	4416
R-squared	0.0330	0.2422
Adj R^2	0.0257	0.2279
F-stat	8.0313***	10.86***
Year Dummies	Yes	Yes

p-values are in parentheses, *** p<.01, ** p<.05, * p<.1, p-values are robust to serial correlation and heteroskedasticity.

4.2 Alternative Measures of Fin tech

Table 5 presents an analysis of the relationship between various measures of Fin tech engagement and the Credit risk distance (CRD) of financial institutions, employing robust fixed effects models with and without control variables. The two alternative measures of Fin tech engagement under consideration are Fin tech per Capita and Fin tech/GDP, offering insights into the impact of Fin tech on financial stability from different perspectives.

Models 1 and 2 reveal a comprehensive picture of how Fin tech integration influences financial stability. Model 1, without control variables, establishes a basic relationship between Fin tech per Capita and CRD, showing a positive and statistically significant coefficient (0.0002), suggesting that an increase in Fin tech adoption on a per capita basis leads to a marginal increase in the CRD, implying a reduced default risk. The economic intuition behind this relationship can be understood through financial inclusion and efficiency gains. As Fin tech services become more accessible to a wider population, they can enhance financial literacy (Panos & Wilson, 2020), provide alternative credit sources, and improve the overall efficiency of financial transactions (Thomas & Hedrick-Wong, 2019), which in turn could bolster the financial stability of institutions (Demirgüç-Kunt et al., 2018).

Model 2 adds several control variables, including leverage, firm size, profitability, among others, to the analysis. Despite the introducing control variables, the positive impact of Fin tech per Capita on CRD strengthens (coefficient of 0.0003) in line with Balyuk et al., (2023), underscoring the robustness of Fin tech's positive effect on financial stability. This enhanced effect could be attributed to the role of Fin tech in diversifying financial services and promoting more personalized and efficient financial solutions (Gomber et al., 2018), which could reduce the operational risks and improve the resilience of financial institutions (Philippon, 2016). The control variables themselves, such as leverage and firm size highlight the importance of sound financial and operational management in mitigating default risks (Ji et al., 2022; Chernobai et al., 2011). The significant coefficients associated with the control variables in Model 2 also offer insights into the broader determinants of CRD. For instance, the negative coefficient for leverage reaffirms the conventional wisdom that higher leverage is associated with higher financial risk (Akhtar et al., 2022; Bressan, 2018), necessitating careful debt management strategies to safeguard against default. Similarly, the effect of firm size on CRD suggests that the structural and operational characteristics inherent to larger banks might have distinct implications for their risk profiles. Larger banks, while benefiting from economies of scale and potentially greater access to capital markets, also face challenges related to complexity and bureaucratic inefficiencies. These challenges can affect their agility and responsiveness to financial stress, potentially increasing their default risk (Anagnostopoulos, 2018).

Correspondingly, Models 3 and 4 in the analysis introduce Fin tech/GDP as a measure to assess the impact of Fin tech on the financial stability of institutions, specifically looking at the Credit risk distance (CRD). Model 3, without controls, and Model 4, with controls, both demonstrate a significant positive relationship between Fin tech/GDP and CRD, indicated by substantial and statistically significant coefficients (15.0231 and 20.5531, respectively) suggesting that as Fin tech becomes a larger part of the GDP, indicating deeper integration into the economy, it positively impacts the financial stability of institutions. This effect could stem from several factors. Firstly, a larger Fin tech sector could imply more innovation in financial services, leading to better risk management tools (Murinde et al., 2022), more efficient capital allocation (Xie & Zhu, 2022), and enhanced access to finance for both individuals and businesses (Bollaert et al., 2021). Secondly, the growth of Fin tech within the GDP might also reflect a diversification of financial services (Kanga et al., 2022), reducing the reliance on traditional banking and spreading risk across a wider array of financial products and services (Claessens et al., 2018). The control variables included in Model 4 remain consistent in their impact on CRD as seen in previous models. The consistency across models underscores the robustness of the analysis and the multifaceted nature of financial stability, which is influenced by both macroeconomic factors like Fin tech's role in the economy and microeconomic factors like individual banks' financial health and management practices.

ALTERNATIVE MEASURES OF FIN TECH

Table 5: Relationship between Alternative Measures of Fin tech and Credit risk distance

Dep. Var.: Credit risk distance	Robust Fixed Effect Model (Without Controls)	Robust Fixed Effect Model (With Controls)	Robust Fixed Effect Model (Without Controls)	Robust Fixed Effect Model (With Controls)
	(1)	(2)	(3)	(4)
Fin tech per Capita	0.0002***	0.0003***		
	(0.0001)	(0.0000)		
Fin tech/GDP			15.0231***	20.5531***
			(0.0001)	(0.0000)
Leverage		-1.4249***		-1.4249***
		(0.0000)		(0.0000)
Firm Size		-0.0443***		-0.0443***
		(0.0080)		(0.0080)
Profitability		1.6001		1.6001
		(0.2438)		(0.2438)
Working Capital		0.1249**		0.1249**
		(0.0453)		(0.0453)
Sales Variation		0.5528*		0.5528*
		(0.0976)		(0.0976)
Loan Loss Provisions		0.0093***		0.0093***
		(0.0010)		(0.0010)
Non-performing Loans		***-0.0204		***-0.0204
		(0.0067)		(0.0067)
Constant	***-0.6275	***1.1637	***-0.6333	***1.1557
	(0.0000)	(0.0004)	(0.0000)	(0.0004)
Observations	4505	4416	4505	4416
R-squared	0.0330	2422.	0.0330	0.2422
Adj R^2	0.0257	2279.	0.0257	0.2279
F-stat	***8.0313	***10.86	***8.0313	***10.86
Year Dummies	Yes	Yes	Yes	Yes

p-values are in parentheses, *** p<.01, ** p<.05, * p<.1, p-values are robust to serial correlation and heteroskedasticity.

4.3. Sub-Sample Analysis :

Table 6 presents the sub-sample analysis where we compared distressed banks with high-leveraged and low leveraged banks and large sized versus small-sized banks. For distressed banks, the positive and significant coefficient for Fin tech (0.0451) indicates that Fin tech credit has a pronounced positive impact on their CRD, suggesting that Fin tech could play a critical role in enhancing the financial stability of these banks. The significance of this finding lies in the potential of Fin tech solutions to provide alternative financing, improve risk assessment, and introduce innovative financial products that can mitigate the risks associated with distressed financial conditions. This aligns with the argument that technological innovation in finance can contribute to financial stability by offering diversified lending channels and enhancing the efficiency of financial services (Lee et al., 2021; Feng et al., 2022). The negative coefficient for leverage (-1.4249) reinforces the established notion that higher leverage ratios are associated with increased default risk, emphasizing the precarious position of distressed banks that typically operate with higher levels of debt. The significant impact of leverage on CRD underscores the need for distressed banks to manage their debt levels carefully, especially in an era where Fin tech innovations offer new opportunities and challenges for financial management (Murinde et al., 2022).

In the context of highly leveraged banks, the Fin tech coefficient (0.0318) remains positive but with a lower magnitude compared to distressed banks, indicating that while Fin tech positively impacts these banks' CRD, the effect is somewhat muted. This could be due to the high leverage overshadowing the potential benefits that Fin tech might offer in terms of financial stability. The stark contrast in leverage's impact between highly leveraged (significantly negative) and low leveraged banks (not significant) further illustrates how debt levels can influence the effectiveness of Fin tech in improving financial stability. Contrarily, low leveraged banks exhibit a stronger positive relationship between Fin tech and CRD (0.0450), suggesting that banks with healthier leverage ratios are better positioned to leverage Fin tech for enhancing financial stability (Tang et al., 2024). This might be due to lower debt levels allowing these banks to more effectively invest in and adopt Fin tech solutions, thereby realizing greater benefits in terms of risk management and operational efficiency (Demirgüç-Kunt et al., 2018).

For large-sized banks, the Fin tech coefficient (0.0472) suggests a robust positive impact of Fin tech on CRD, potentially reflecting the capacity of larger banks to invest in and integrate Fin tech solutions into their operations, thereby improving their risk profile and financial stability (Boot et al., 2021). The significant negative coefficient for leverage (-1.4752) and the effects of firm size and profitability underscore the complex interplay between bank characteristics and the impact of Fin tech on financial stability. Conversely, small-sized banks also benefit from Fin tech (0.0434), indicating that Fin tech's impact on financial stability is not confined to larger institutions (Fung et al., 2020). This could reflect the agility of smaller banks in adopting and integrating Fin tech innovations, potentially offsetting their scale disadvantages. The significant negative impact of leverage (-0.9756) across both bank sizes highlights the universal importance of managing leverage to enhance financial stability.

Table 6: Relationship between Fin tech and Credit risk distance (Distressed Banks, high vs. low leveraged banks, and large vs. small-sized banks)

Dep: Credit risk distance	Distressed Banks (1)	Highly Leveraged Banks (2)	Low Leveraged Banks (3)	Large-sized Banks (4)	Small-sized Banks (5)
	Robust Fixed Effect Model				
Fin tech	0.0451***	0.0318*	0.0450**	0.0472***	+0.0434***
	(0.0000)	(0.0583)	(0.0456)	(0.0036)	(0.0079)
Leverage	-1.4249***	-1.7010***	0.3467	-1.4752**	-0.9756***
	(0.0000)	(0.0000)	(0.6920)	(0.0194)	(0.0077)
Firm Size	-0.0443***	-0.0354*	-0.0085	-0.0417*	-0.0446*
	(0.0080)	(0.0770)	(0.8604)	(0.0809)	(0.0825)
Profitability	1.6001	3.1478	2.5436	.742	3.6861*
	(.2438)	(.1643)	(.1539)	(.7752)	(.0733)
Working Capital	.1249**	.124	.1261	.3415*	.0536
	(.0453)	(.2056)	(.2135)	(.0863)	(.124)
Sales Variation	.5528*	.3741	.6316*	1.1913**	-.1013
	(.0976)	(.6272)	(.0752)	(.0324)	(.8393)
Loan Loss Provisions	.0093***	.0054	.0124***	.0066*	.0075*

Follow : Table 6: Relationship between Fin tech and Credit risk distance (Distressed Banks, high vs. low leveraged banks, and large vs. small-sized banks)

Dep: Credit risk distance	Distressed Banks (1)	Highly Leveraged Banks (2)	Low Leveraged Banks (3)	Large-sized Banks (4)	Small-sized Banks (5)
	(.001)	(.1451)	(.0005)	(.0895)	(.0576)
Non-performing Loans	-0.0204***	-0.0284***	-0.0277*	**-0.0183	-
	(.0067)	(.0006)	(.0621)	(.0365)	
Constant	.0979	.5525	-1.8291**	.1729	-.3361
	(.7735)	(.2037)	(.0441)	(.7033)	(.5096)
Observations	4189	2414	1955	2850	1548
R-squared	.2422	.3123	.214	.3945	.1986
Adj R^2	.2279	.2862	.183	.3714	.1697
F-stat	10.86	12.7513	3.8752	7.9503	6.9217
Year Dummies	Yes	Yes	Yes	Yes	Yes

p-values are in parentheses, *** p<.01, ** p<.05, * p<.1, p-values are robust to serial correlation and heteroskedasticity.

SUB-SAMPLE ANALYSIS

4.4 Endogeneity Checks

On account of endogeneity issues, we tested our model using system generalized method of moments (S-GMM) estimator to check for potential simultaneity, heterogeneity, and endogeneity as reported in the Table 7. The results remain qualitatively similar for explaining the relationship between Fin tech credit and CRD of global banks. Across all models, the lagged CRD variable shows a highly significant positive coefficient, indicating the persistence of financial stability over time suggesting that past financial health significantly influences current stability, underscoring the importance of historical financial performance in predicting future default risk. The robust significance across models (with p-values at 0.0000) confirms the dynamic nature of financial stability and highlights the role of cumulative financial decisions and outcomes in shaping a bank's risk profile (Blundell & Bond, 1998).

The positive and significant coefficients for Fin tech credit and Fin tech per Capita across their respective models signal that increased Fin tech activity, whether in overall lending or on a per capita basis, contributes positively to financial stability implying that Fin tech's innovative lending practices and financial services positively affect banks' default risk, potentially by enhancing access to credit, diversifying financial products, and improving risk management practices (Demirgüç-Kunt et al., 2018). In the model examining Fin tech/GDP, the significant coefficient further underscores the substantial impact of Fin tech's economic presence on financial stability. As Fin tech becomes a more integral part of the economy, its contributions to efficiency, inclusivity, and innovation within the financial sector become increasingly pivotal in enhancing the resilience of financial institutions (Thakor, 2020).

The mixed results for leverage, firm size, and sales variation across models suggest that while these factors influence CRD, their impact is nuanced and may vary depending on other concurrent factors. Notably, profitability, working capital, loan loss provisions, and non-performing loans exhibit significant relationships with CRD, indicating that effective profitability management, prudent working capital practices, and diligent credit risk management are essential for maintaining financial stability. Concerning diagnostic tests, the AR(1) and AR(2) tests, along with the Sargan-Hansen statistic, provide confidence in the model's specification and the validity of the instruments used. The lack of second-order autocorrelation (as indicated by AR(2)'s p-values) and the acceptance of the instrument validity (through Sargan-Hansen tests) underscore the robustness of the GMM estimation in capturing the dynamic relationship between Fin tech metrics and financial stability.

ENDOGENEITY TEST:

Table 7: Relationship between Fin tech and Credit risk distance

(System GMM Estimation)

	Credit risk distance		
	Fin tech credit (1)	Fin tech per Capita (2)	Fin tech/GDP (3)
Lagged Credit risk distance	0.7979***	0.8118***	0.8073***
	(0.0000)	(0.0000)	(0.0000)
Fin tech credit	0.0092***		
	(0.0028)		
Fin tech per Capita		0.0001***	
		(0.0001)	
Fin tech/GDP			8.4548***
			(0.0001)
Leverage	-0.2515	-0.2521	-0.2544
	(0.1976)	(0.1754)	(0.1774)
Firm Size	0.0011	-0.0009	-0.0006
	(0.8633)	(0.8830)	(0.9200)
Profitability	3.7427**	3.5776**	3.6402**
	(0.0140)	(0.0174)	(0.0168)
Working Capital	-0.0124**	-0.0125**	-0.0127**
	(0.0486)	(0.0425)	(0.0418)
Sales Variation	0.1468	0.1868	0.1683
	(0.7621)	(0.6981)	(0.7280)
Loan Loss Provisions	0.0091***	0.0097***	0.0096***
	(0.0027)	(0.0013)	(0.0015)
Non-performing Loans	0.0139**	0.0124**	0.0128**
	(0.0201)	(0.0356)	(0.0311)
Constant	-0.1462	0.0939	0.0880
	(0.4947)	(0.6685)	(0.6914)
Observations	4476	4476	4476

Follow: Table 7: Relationship between Fin tech and Credit risk distance

	Credit risk distance		
	Fin tech credit (1)	Fin tech per Capita (2)	Fin tech/GDP (3)
F-stat	7722.42***	8051.63***	7911.70***
AR(1)	0.000***	0.000***	0.000***
(AR(2	0.941	0.994	0.998
Sargan-Hansen	0.825	0.769	0.807
Year Dummies	Yes	Yes	Yes

p-values are in parentheses, *** p<.01, ** p<.05, * p<.1, p-values are robust to serial correlation and heteroskedasticity.

Our empirical findings indicate that increased Fin tech credit is associated with a higher Credit Risk Distance (CRD), suggesting that bank risk has decreased rather than intensified. This outcome contrasts with earlier theoretical expectations that framed Fin tech competition as a destabilizing force. A likely explanation lies in the adaptive behavior of incumbent banks: many have recalibrated their lending models, embraced digital transformation, and adopted advanced data analytics to more accurately assess and price borrower risk. In addition, evolving regulatory frameworks and strategic collaborations with Fin tech firms may have created new mechanisms for managing risk, allowing traditional banks to integrate technological innovation without sacrificing prudential oversight. In this context, the competitive pressure exerted by Fin tech may no longer be inherently destabilizing but instead serves as a catalyst for institutional modernization. As such, our results suggest a paradigm shift, Fin tech is not merely a disruptive competitor but a transformative influence driving improved risk management across the banking sector.

5. Conclusion and Implications :

As Fin tech continues to grow at an unprecedented pace, its integration into traditional financial systems raises questions about its impact on the stability of these systems. Given the aftermath of the 2008 financial crisis, understanding factors that contribute to or detract from financial stability is paramount. Meanwhile, Fin tech has the potential to significantly enhance financial inclusion by reaching underserved or unbanked populations, thereby changing the traditional banking customer base and creating new markets. Moreover, regulatory bodies and policymakers face the challenge of keeping pace with rapid technological advancements to ensure that the financial sector remains robust against potential shocks. Given this, we examined the relationship between Fin tech credit and the financial stability of banks, measured through Credit risk distance (CRD) for 685 global banks over the period 2013-2019. By utilizing baseline regression, robust fixed effects, and System GMM estimation techniques, the study offers a comprehensive understanding of how Fin tech credit, both in absolute terms and relative to economic metrics like GDP and per capita basis, impacts bank stability.

The findings reveal a consistent positive impact of Fin tech credit on banks' CRD across various models and sub-samples, including distressed and highly leveraged banks, as well as large and small-sized institutions. This suggests that Fin tech credit contributes to reducing the probability of default among banks, potentially through improved access to finance, diversification of financial products, and enhanced efficiency in financial services. The study also highlights the importance of internal financial practices, such as leverage management, profitability, and working capital, in influencing banks' financial stability in the context of Fin tech adoption.

The study informs various practitioners and academics through useful implications. For policymakers, the demonstrated positive relationship between Fin tech and bank stability highlights a pressing need to create regulatory frameworks that ensure financial system integrity. Such a regulatory environment should aim to encourage the development and integration of Fin tech solutions while instituting safeguards against potential risks associated with these technologies. This delicate balance is crucial in promoting a robust financial sector capable of leveraging technological advancements for improved service delivery and risk management. Practitioners and banks stand to benefit significantly from the strategic adoption of Fin tech solutions. The study's findings suggest that banks incorporating Fin tech into their operations can enhance their resilience against defaults and improve their competitive edge in the rapidly evolving financial marketplace by adopting new lending platforms, leveraging data analytics for better risk assessment, or offering innovative customer services that meet the demands of a digitally savvy clientele.

Investors and customers, as crucial stakeholders in the financial ecosystem, can utilize the insights from this study to make informed decisions. Investors might assess the stability and innovative capacity of financial institutions as indicators of long-term viability and growth potential. Customers, on the other hand, might look for institutions that successfully harness Fin tech to offer secure, efficient, and user-friendly services, thereby indicating a forward-thinking and stable provider. Academic researchers are provided with a foundational basis for further inquiry into the complex interplay between technology and financial stability. The dynamic and multifaceted nature of Fin tech's impact offers a rich field for exploration, ranging from the effects of specific technologies like blockchain and artificial intelligence on banking operations to the broader socioeconomic implications of increased financial access and efficiency.

This study provides new insights into the relationship between Fin tech credit and bank risk by analyzing a multi-country panel dataset using Credit Risk Distance (CRD) as the main outcome variable. However, several limitations should be acknowledged that offer directions for future research.

First, the study employs the Altman Z-score as a proxy for credit risk, which, although widely used, was originally developed for industrial firms. While it has proven effective in recent financial studies, more tailored measures such as the bank Z-score or risk-weighted assets could offer additional precision. Incorporating these would require a redesign of the empirical framework and estimation strategy, which lies beyond the scope of the present analysis.

Second, while the model includes a robust set of financial and institutional controls, several additional variables proposed in the literature, such as revenue diversification, cost-to-income ratio, capital adequacy ratios, and loan growth, were not included due to time constraints in extending the analytical model. These variables represent important dimensions of bank-level behavior and risk exposure and could be examined in future research to deepen the understanding of transmission channels.

Third, at the macroeconomic level, although our empirical specification incorporates country-year fixed effects to capture unobserved heterogeneity, further refinement could be achieved by incorporating specific institutional variables such as deposit insurance regimes, capital requirement thresholds, and measures of banking market concentration. These factors may interact with Fin tech development in complex ways, influencing risk behavior across jurisdictions.

Lastly, market-based measures of risk, such as equity volatility and earnings volatility, were not employed due to the presence of unlisted banks in the sample and the cross-country structure of the data. These indicators may offer valuable complementary insights, particularly in studies focused on listed institutions or single-country settings.

Future research could build upon this work by employing richer and more granular datasets to incorporate the abovementioned variables. Comparative studies across developed and emerging markets, or bank-level case studies with detailed balance sheet data, may yield further understanding of how Fin tech reshapes risk dynamics in different regulatory and economic environments. Additionally, longitudinal studies capturing post-pandemic shifts in digital adoption and credit risk transmission could provide timely and policy-relevant insights.

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