South African Reserve Bank

Working Paper Series

WP/25/08

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Authorised for publication by Konstantin Makrelov

4 August 2025

SOUTH AFRICAN RESERVE BANK

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Fintech and financial system stability in South Africa

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Abstract

In this paper we examine the relationship between fintech formations and the default risk and performance of incumbent financial institutions in South Africa. We find that the development of fintech startups is associated with lower bankruptcy risk, credit risk and stock return volatility among banks and other financial institutions. Fintech startup formations are also associated with improvement in incumbent institutions' performance. Further analysis shows that the risk reduction effect of fintech development is more pronounced for smaller banks. Overall, our results are consistent with the assertion that fintech formations generally improve risk management efficiency and reduce incumbent financial institutions' default risk. However, the relationship is nonlinear, suggesting that the initial collaboration, which reduces default risk, can turn into increased competition as more fintech startups enter the market. From a policy standpoint, efforts to promote more collaboration should be encouraged, but regulators need to be cautious of potential systemic risk.

JEL classification

G32, G21, G23, Q55

Keywords

Fintech, financial institutions, default risk, performance, financial stability

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1. Introduction

South Africa's financial system, one of the most developed markets in the developing world (IMF 2022; World Economic Forum 2016), has experienced significant growth in fintech formation and financial innovation over the past two decades. Several fintech firms have entered the banking environment to 'disrupt' traditional modes of fintech solutions. Fintech firms provide a myriad of complex offerings, ranging from digital payments solutions and information services to more straightforward savings and deposit-taking products, online banking facilities, securities trading and financial software (Dapp 2014). This presents rich opportunities for potential collaboration and competition between fintech firms and incumbent financial sector firms in South Africa's financial markets. From a policy standpoint, it raises an important question about whether fintech development enhances or impedes the stability of financial systems in the country.

In this paper, we examine the effects of fintech development on the stability of the financial system in South Africa. We first focus on banks, the key players of the financial system, and find that fintech positively affects the banks' Z-score (our measure of default risk). Fintech formations are not only associated with lower risk but may also reduce the risk of default. However, we find that the relationship between fintech formation and bank default risk is nonlinear, as the coefficient of fintech is consistently positive and that of $fintech^2$ is consistently negative, suggesting a U-shaped relationship between fintech formation and bankruptcy risk. Although fintech formation reduces banks' bankruptcy risk, the effect is heterogeneous. It reduces the bankruptcy risk of small banks but has the opposite effect on large banks. The results are consistent with the argument that smaller banks benefit more from fintech formations (Haddad and Hornuf 2021). Fintech formations also positively affect the Z-score of non-bank financial institutions in South Africa.

We also examine the source of the changes in risk and find that risk is reduced when profitability and the equity-to-assets ratio improve. At the same time, fintech formation accentuates banks' risk through increased profit variability. On balance, however, the improvement in profitability and equity outweighs the increase in profit variability.

Lastly, we investigate the effects of fintech formations on the performance of the financial sector and find that it positively impacts return on assets (ROA), stock market returns and Tobin's Q of financial institutions in South Africa. Our results are robust to using aggregate data and different estimation methods, to controlling for the effects of the global financial crisis and to using alternative measures of default risk.

Our study contributes to the literature on the impact of fintech. A growing number of studies examine the effects of fintech and financial innovation on the performance and stability of financial institutions. Phan et al. (2020) investigated a sample of 41 Indonesian banks and found that fintech development negatively predicts bank performance. Haddad and Hornuf (2021) studied the effect of fintech startups on the performance and default risk of traditional financial institutions from 87 countries and found a significantly positive impact of fintech development on financial institutions' performance. Our study shows that the fintech formation-financial institution nexus is nonlinear. In the early stages, fintech formation reduces default risk, suggesting initial beneficial collaboration with incumbent financial institutions. However, as more fintech startups enter the market, competition increases, squeezing incumbent margins. Thus, our study corroborates that of Wang, Liu and Luo (2021), which shows that there is a nonlinear relationship between fintech formation and the performance of financial institutions over time.

The rest of the paper is structured as follows. The state of fintech development in South Africa is presented in section 2. Background review and hypotheses appear in section 3, while data and methodology are discussed in section 4. We present the results and robustness tests in section 5, and section 6 concludes the study.

2. The state of fintech in South Africa

South Africa has a fast-growing fintech industry. As of December 2021, over 200 fintech firms were operating in the country,[1] and the number is expected to grow because of the support from innovation hubs and the increasing adoption of technology in financial services. Regulators have created a conducive environment for fintech to thrive. For example, the South African Reserve Bank (SARB) has established the

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[1] Retrieved from Crunchbase website: https://www.crunchbase.com/

Financial Technology Programme, which assesses the development of fintech and the attendant regulatory implications for the country. The fintech landscape in South Africa is segmented into eight functional areas: payments, lending, savings and deposits, insurtech, investments, financial planning and advisory, capital raising and business-to-business technology providers (see Genesis Analytics 2019 for details).

Most of the fintech firms have identified consumer pain points and developed simple solutions that reduce the friction experienced in traditional financial services processes. Their ability to innovatively use technology to find alternative solutions to banking clients' needs is putting pressure on incumbent retail banks (Dapp 2015; Coetzee 2019). The traditional banks realise that the disruption by these non-traditional competitors is threatening their survival (Absa Bank Ltd 2016; Nedbank Group Ltd 2016; Standard Bank Group Ltd 2016; FirstRand Group Ltd 2017). The results from a PwC survey in South Africa show that the banking and payments industries are feeling the most pressure from fintech companies. Two thirds (67%) of financial services firms surveyed ranked pressure on profit margins as the top fintech-related threat, followed by loss of market share (59%) (PwC 2016).

The threat to incumbents' operating models and the increased competition can negatively affect profitability, resulting in threats to systemic stability (Arner, Barberis and Buckley 2015; Coetzee 2019). Similarly, there is evidence that fintech firms are partnering with banks and other financial institutions, which creates systemic risks because of potential disruptions to these third-party services (Deloitte 2017). On the other hand, collaboration brings about potential synergies between fintech and traditional financial institutions.

3. Related literature

3.1 Theoretical background

The rise of fintech presents potential dangers to the stability of the financial system. The effects of fintech on financial system stability can be partly explained by the disruptive innovation theory (Christensen 1997) or the innovation-fragility hypothesis of Beck et al. (2016). The disruptive innovation theory posits that new entrants that apply innovative technology to provide more accessible and cost-effective products can intensify competition in the market. Faced with increased competition and declining profitability, banks may take excessive risks, which can induce financial instability (Marcus 1984; Keeley 1990). A recent study by the World Bank echoes the point that competitive pressure from fintech firms could change the behaviour of incumbents, including taking on more risk as they seek to compensate for revenue losses (Feyen, Natarajan and Saal 2023).

Research also shows that fintech products can substitute or complement existing banking and non-banking financial products (Kommel, Sillasoo and Lublóy 2019). More traditional financial institutions that use old systems are found to be slow to adopt new technology, while the new market entrants benefit from a lack of legacy infrastructure, low levels of organisational complexity and a less restrictive regulatory framework, which allows them to be more agile and to innovate faster (Laven and Bruggink 2016; Brandl and Hornuf 2020). Therefore, in an era of increased competition from fintech firms, traditional banks and other financial institutions are likely to cede some business activity to these technologically savvy entrants (Wang, Liu and Luo 2021).

The innovation-fragility hypothesis of Beck et al. (2016) predicts higher bank fragility in environments with higher levels of financial innovation. Partnerships with fintech and telecommunications companies can cause counterparty risk, and the attendant domino effects on other players in the financial system can potentially increase systemic risks. A study by the International Monetary Fund (IMF) shows that technology that facilitates instantaneous bank transfers and withdrawals may also boost the speed of bank runs (Bakker et al. 2023). Meanwhile, partnerships with fintech firms can increase cyber-risk. A big tech firm that provides third-party services to many financial institutions, such as data storage, transmission or analytics, could pose a systemic risk if there is an operational failure or a cyberattack. The susceptibility of financial activity to cyberattacks is higher when the systems of different institutions are connected, among which there could be a weak link. Thus, greater use of technology and digital solutions expands the range and number of entry points cyber-hackers might target (Deloitte 2017).

3.2 Empirical research

Similar to the theoretical findings, empirical research on the relationship between financial innovation (fintech) and financial system stability has broadly yielded conflicting results. Kommel, Sillasoo and Lublóy (2019) show that the financial products and services that fintech firms provide are often similar to those of the incumbents, implying greater scope for substitution and thus competition. Given their agile nature, fintech firms are able to absorb the existing business of traditional market players in the financial sector, where the latter operate less efficiently, thereby reducing domestic banks' profitability and franchise value (Hellmann, Murdock and Stiglitz 2000). Indeed, recent research shows that fintech competitors have taken market share from traditional banks and broadened access to borrowers previously underserved by banks (Feyen, Natarajan and Saal 2023). Consistent with the franchise value effect of increased competition, the proliferation of fintech is associated with a reduction in lending spreads (Bakker et al. 2023) and reduced profitability (Phan et al. 2020). In these conditions, an increase in competition can push banks to take more risks; for example, loan officers could lower their credit standards to maintain or increase market share, which could increase non-performing loans (NPLs) (Mohsni and Otchere 2014).

On the other hand, fintechs help financial institutions improve their risk management strategy through big data analytics (Chen, You and Chang 2021), enhance their cybersecurity protocols, help detect electronic fraud and prevent potential malicious actions (Gupta and Mandy 2018). In addition, fintech involvement in finance could lead to a more diverse, competitive and stable financial system. Fintechs can improve competition and financial inclusion, exert welcome pressure on incumbent financial institutions to innovate and boost the overall efficiency of financial services. Research also shows that information technology helps reduce banks' transaction costs and improve service quality. In addition, collaboration between banks and fintech firms enables financial institutions to capitalise on the fintech innovation advantages to increase the number of customers and provide additional services (Acar and Çitak 2019; Hornuf et al. 2021; Wang, Liu and Luo 2021). The resulting improvement in risk management, along with enhanced profitability, can make financial institutions more stable.[2]

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[2] Other researchers find that fintech does not affect banks' performance because they typically attract a particular clientele that traditional financial institutions do not serve (Haddad and Hornuf 2021).

In summary, although fintech firms have created new opportunities to make financial systems more efficient, they have also created challenges that affect financial stability (Tobias 2021; Teima et al. 2022; Feyen, Natarajan and Saal 2023). Their expansion into financial services and increasing interconnectedness with traditional banks can create risks to financial stability (Bains, Sugimoto and Wilson 2022). The preceding discussion suggests that the impact of fintech formation on financial institutions' risk and performance is an empirical issue.

4. Data and methodology

4.1 Data and measures

This study covers the period 1998–2020, which coincides with an era when South Africa experienced significant growth in fintech firms (see Figure 1). To examine the impact of financial innovation on financial system stability in South Africa, we use the number of fintech firms as a proxy for financial innovation. Phan et al. (2020) and Haddad and Hornuf (2021) also use this variable as a proxy for financial innovation to examine the effect of fintech on bank performance and financial institutions' default risk. Overall, we identified 147 fintech firms over our study period. As Figure 1 shows, the past decade has witnessed strong growth in these firms in South Africa.

The sheer increase in fintech entrants and innovators is indicative of competitive pressures on traditional providers (Feyen, Natarajan and Saal 2023). Given that the activities of fintech firms may also affect other financial institutions beyond banks, we assess the impact of fintech formation on the default risk and performance of banks and non-bank financial institutions. The data on fintech firms are obtained from the Crunchbase database. This database has been used by various researchers, including Bernstein, Korteweg and Laws (2017); Didier et al. (2022); and Bakker et al. (2023). While the database does not provide granular information on the type of fintech firms, Genesis Analytics (2019) shows that the bulk of the fintech activity in South Africa is centred on payment (30%), consistent with the global trend documented by the IMF (see Didier et al. 2022), followed by business-to-business technology support (20%) and lending (12%), investment (10%), insurtech (9%), financial planning advisory (7%) and savings and deposits (6%). Financial statements and stock returns were obtained from the Compustat World Database. Data availability limited our sample size to 70 banks and non-bank financial institutions.

To test our main hypothesis, we use accounting and market measures of risk in our analysis. We follow Laeven and Levine (2009) and Houston et al. (2010) and use the Z-score to measure financial institutions' default risk. The Z-score, which is widely used as a measure of bank distance to default, is expressed as follows:

$$Z{-}score = (ROA) + (E/TA))/\sigma ROA \tag{1}$$

where *ROA* represents the return on assets, E/TA is the equity-to-total-assets ratio, and *σROA* is the standard deviation of ROA. The *Z-score* combines profitability, leverage and return volatility in a single measure, and it measures the number of standard deviations that returns have to fall to diminish equity. The score increases as profitability and capitalisation levels improve and falls with an increase in the variability of ROA. A higher Z-score implies a lower default risk and greater financial institution stability. We use a three-year moving window to estimate the standard deviation of ROA. The approach involves dropping the earliest ROA each time. Thus, the variable varies from year to year.

We also consider the volatility of stock returns as a measure of financial institution risk. This measure, which has been widely used by prior researchers, including Haddad and Hornuf (2021) and Sun and Liu (2014), captures the market's perception of the risk inherent in banks' assets, liabilities and off-balance-sheet positions (Pathan 2009). For robustness tests, we follow prior studies and use the standard deviation of the ROA (Laeven and Levine 2009; Lepetit et al. 2008) and the ratio of NPLs to total loans (Jiménez, Lopez and Saurina 2013) as additional measures of risk. To test our hypothesis relating to performance, we employ the net interest margin, ROA and Tobin's Q as measures of financial institutions' performance. Tobin's Q is measured as the sum of the market value of equity and the book value of liabilities, all divided by the book value of assets. Following Anilowski, Feng and Skinner (2007), we use annual stock returns as our market-based performance measure.

4.2 Methodology

To ascertain the relationship between fintech formation and financial stability, we follow Phan et al. (2020) and Haddad and Hornuf (2021) and estimate a panel regression of the general form:

$$Risk_{i,t} = \alpha_i + \beta_1 LnFinTech_t + \beta_2 Risk_{i,t-1} + \sum_{n=4}^{M} \beta_n CONTROLS + \varepsilon_{i,t} \qquad (2)$$

where *Risk* is one of the stability measures for firm i at time t. In the performance regressions, we replace *Risk* with performance, where the variable represents one of three dependent variables: ROA, annual stock returns or Tobin's Q. $FinTech_t$ is the number of fintech firms at time t. To deal with the skewness in the distribution of this variable, we use the natural logarithm of the number of fintech companies. A negative sign on the coefficient of fintech implies that the development of fintech firms bodes ill for the incumbent financial institutions and, hence, the financial system's stability. On the other hand, a positive coefficient implies that fintech firms make financial institutions more stable, while $\varepsilon_{i,t}$ is the error term.

To account for financial institution heterogeneity, we include several control variables. Following Pathan and Faff (2013) and Berger and Bouwman (2017), we include firm size, capital ratio, leverage, cost-to-income ratio, interest income share and net income growth rate as control variables. Firm size is proxied by total assets, and it is expected to have a negative impact on the Z-score given that the larger the bank, the greater the likelihood that it is subject to 'too big to fail' tendencies. Additionally, fintech formation is likely to hurt the performance and stability of large firms that are not agile enough. On the other hand, large banks can earn higher profits by lowering deposit rates and maintaining higher lending rates in a non-competitive environment (Flamini, Schumacher and McDonald 2009). The income growth rate accounts for differences in risk preferences across banks and is expected to have a negative effect on the Z-score, our key risk measure. The capital ratio is included as a control variable because extant literature shows that higher capital is a positive signal of a bank's prospects, indicating that they do not require external funding (Berger 1995) and are more profitable. Thus, the variable can impact firms positively, making them less risky. Interest income share can negatively impact bank profitability if the share of interest income relative to total income is high (Dietrich and Wanzenreid 2014) since, in general, banks obtain higher margins from asset management activities (Phan et al. 2020).

We also control for macroeconomic effects on the performance and risk of financial institutions. Prior research, including Trujillo-Ponce (2013), shows that inflation can adversely affect bank profits and induce higher risk-taking. The state of the economy can affect the quality of banks' loan portfolios, profitability and stability. In addition, prior literature shows that economic growth stimulates the financial system (Demirgüç-Kunt and Huizinga 1999). We therefore include inflation and the gross domestic product (GDP) growth rate as control variables.

The dynamic nature of equation 1 allows us to account for the fact that the stability of the financial sector (our dependent variables) might be time-persistent. However, including Z-score$_{t-1}$ among the right-hand-side variables will lead to inconsistent parameter estimates when firm heterogeneity is accounted for using conventional fixed- or random-effects estimators (Baltagi 2001). Moreover, equation 2 can be affected by other endogenous regressors and reverse causality issues. In particular, the state of the financial sector might have a positive or negative effect on the profitability of financial institutions, which in turn can affect their risk-taking behaviour and the financial system's stability. We follow prior research (such as Shaban and James 2018; Phan et al. 2020) and employ the generalised method of moments (GMM) estimation techniques to address these issues. Specifically, we use a two-step GMM system dynamic panel estimator (Arellano and Bover 1995) to estimate the model. This approach allows us to treat the explanatory variables as endogenous using their past values as instruments (Wintoki, Linck and Netter 2012).[3] Lagged variables are more likely to be exogenous and should be valid instruments (Haddad and Hornuf 2021).

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[3] Although the first-difference GMM controls for possible measurement errors and endogeneity bias, as pointed out by Blundell and Bond (1998), the lagged levels of the explanatory variables are weak instruments for the variables in differences when explanatory variables are persistent. The system GMM estimator (Arellano and Bover 1995) addresses these shortcomings by fully exploiting the cross-firm variation in the data. The system estimator augments the difference GMM by including an equation in levels and by estimating simultaneously in differences and levels, with the two equations distinctly instrumented (Jameaba 2020).

The validity of the instruments is evaluated using the Sargan test of over-identifying restrictions.

5. Results

5.1 Summary statistics

Table 1 presents summary statistics of the dependent, explanatory and control variables. The Z-score, our measure of insolvency risk, has a mean value of 29.3 and a standard deviation of 59.8, indicating that the sample contains both stable and unstable financial institutions. The profitability of the sample, as measured by ROA, averages 2.87%, although there is a wide variation in performance. The net revenue growth averaged 5% during the study period. The NPL ratio, a proxy for credit risk, shows a mean of 2.96%, which is indicative of good loan portfolio management. The correlation matrix is reported in Panel B. We analyse four indicators of financial risk, namely insolvency risk (Z-score), credit risk (NPL), operational risk (standard deviation of ROA) and stock market risk (stock return volatility). The Z-score is positive and significantly correlated with fintech development. This result suggests that fintech growth is associated with lower insolvency risk. Credit risk negatively correlates with profit efficiency, implying that interest revenue declines when NPLs increase.

Table 1: Summary statistics and correlation matrix

This table presents descriptive statistics and a correlation matrix for the variables in our regressions. Panel A reports the descriptive statistics, and Panel B shows the correlation matrix.

Panel A: Descriptive statistics

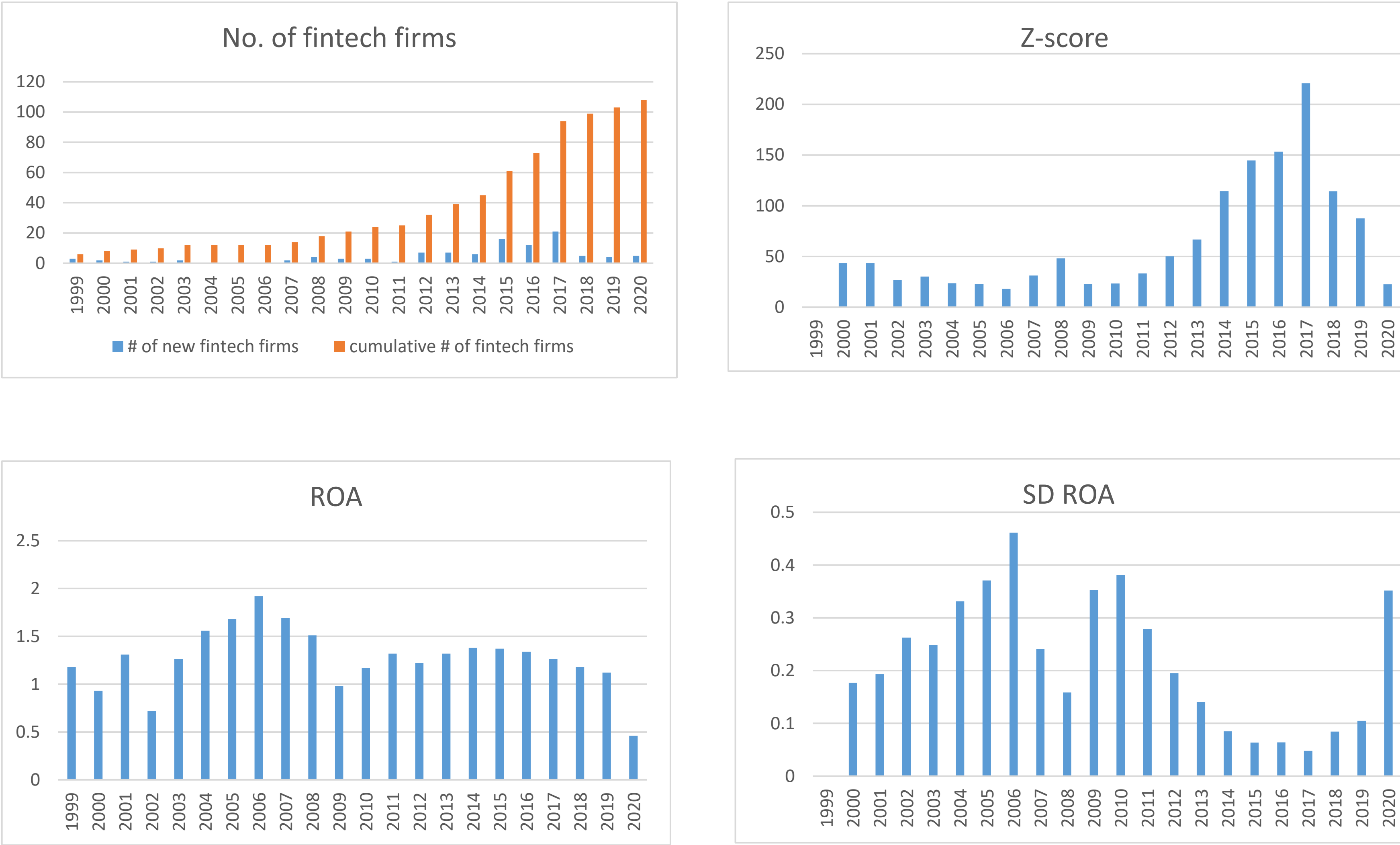
Variable	Mean	Median	Standard deviation	1st quartile	75%	Skewness	Kurtosis
Equity	45 430.674	1 149.000	509 865.873	214.300	8 973.000	15.446	213.676
Size	466 868.050	4 969.400	5 105 357.820	805.300	59 374.200	15.484	215.554
ROE	12.415	15.815	36.386	7.098	24.260	-2.766	23.861
Capital ratio	25.233	19.640	49.306	7.930	41.120	-9.299	120.443
ROA	2.874	2.100	32.154	0.680	7.330	11.220	289.767
SD ROA	8.465	1.645	33.199	0.411	5.797	10.476	110.473
Z-score	29.340	13.212	59.833	4.459	32.540	9.073	115.634
Cost to income	1.174	1.624	17.076	0.553	3.011	-20.596	492.900
Interest income share	0.672	0.071	2.829	0.028	0.576	0.273	49.826
Price to book	2.171	1.652	3.637	1.069	2.626	5.686	87.031
Net income growth	0.049	0.083	6.627	-0.427	0.409	-2.138	112.423
Volatility	56.905	36.270	63.291	27.320	55.110	3.553	16.145
Tobin’s Q	4.818	1.090	28.551	1.010	1.430	10.419	107.235
Stock price return	26.874	6.061	185.808	-13.132	28.130	12.157	127.483
Debt to equity	295.277	144.875	354.744	56.860	341.180	1.659	1.761
NPL ratio	2.958	2.330	4.211	0.016	4.138	4.578	30.416

Panel B: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. ROA	1.00																
2. ROE	0.70	1.00															
3. SD ROA	-0.03	-0.32	1.00														
4. Z-score	0.03	0.10	-0.49	1.00													
5. Ln Z-score	0.12	0.23	-0.78	0.88	1.00												
6. # Fintech	-0.06	-0.21	-0.34	0.43	0.44	1.00											
7. Total assets	-0.38	-0.10	-0.50	0.40	0.47	0.41	1.00										
8. Capital ratio	0.76	0.15	0.41	-0.06	-0.11	0.03	-0.56	1.00									
9. Interest income	-0.10	-0.01	-0.23	-0.04	0.04	0.01	0.19	-0.28	1.00								
10. Cost to income	-0.02	-0.02	0.07	-0.08	-0.07	-0.08	0.06	-0.07	0.74	1.00							
11. Price to book	0.58	0.63	-0.12	0.19	0.21	-0.06	-0.16	0.36	-0.11	-0.14	1.00						
12. Net income growth	0.50	0.69	-0.49	0.13	0.35	-0.04	0.02	0.04	0.01	0.02	0.31	1.00					
13. Debt to equity	-0.07	-0.13	-0.01	-0.04	-0.02	0.04	-0.14	-0.05	0.10	0.06	-0.35	-0.01	1.00				
14. Volatility	-0.24	-0.47	0.47	-0.28	-0.42	0.04	-0.11	0.11	-0.04	-0.02	-0.41	-0.50	0.12	1.00			
15. Tobin's Q	0.68	0.44	0.04	0.12	0.12	0.07	-0.31	0.65	-0.12	-0.11	0.87	0.23	-0.24	-0.27	1.00		
16. Stock returns	0.37	0.28	0.18	-0.06	-0.08	-0.31	-0.30	0.31	-0.12	-0.04	0.40	0.08	-0.22	-0.15	0.35	1.00	
17. NPL ratio	0.34	-0.07	-0.08	-0.09	0.01	0.04	-0.03	0.38	-0.01	-0.20	-0.05	-0.06	0.20	0.21	0.13	0.10	1.00

Figure 1 shows the trend in fintech formations, the Z-score, profitability (ROA) and profit variability across time. We observe growth in the number of fintech firms, especially from 2012 to 2017, followed by a drop in the growth of startup formation. An analogous pattern is also observed for the Z-score and ROA over the same period, where these variables improve with growth in fintech formations and then reduce with decreasing growth in the number of fintech firms. This pattern is also consistent with profit variability, where the standard deviation of ROA reduces with increases in fintech formation. The graphs provide evidence of a positive correlation between fintech formations, the Z-score and ROA, and a negative correlation with the standard deviation of ROA.

Figure 1: Graphs of key variables



5.2 Baseline results

5.2.1 The effect of fintech formation on bank risk-taking

We report the results of our baseline regression in Table 2. Given that the Z-score is highly skewed (Laeven and Levine 2009), we also use the natural logarithm of the Z-score in our estimations. The results are presented for both variants of the Z-score in the first two columns. We find that fintech startup formations in South Africa positively affect the Z-score. However, when using the natural logarithm of the Z-score as the dependent variable, we find that the coefficient of fintech loses significance. These results raise the question of whether the relationship is well-specified.

It is conceivable that the relationship between fintech formation and bank risk-taking is nonlinear. For instance, initial competition between fintech firms and incumbent financial institutions could lead to collaboration. Alternatively, initial collaboration, which reduces risk, can give way to increased competition and increased risk as the number of fintech firms increases. To explore these conjectures, we introduce $fintech^2$ as another independent variable and re-estimate our baseline regression. The results, which are presented in columns 3 and 4 of Table 2, provide evidence of a nonlinear relationship between fintech development and bank risk. In particular, the coefficient of fintech is now consistently positive, while that of fintech^2 is consistently negative and significant in the regressions using both the Z-score and Ln Z-score as the measure of risk. The positive coefficient of fintech and the negative coefficient of fintech^2 suggest that the relationship between fintech and bank risk-taking is U-shaped. Fintech development initially reduces the insolvency risk of banks but then intensifies the risk as the number of fintech firms increases.

These results are consistent with the tenets of the collaboration hypothesis. Faced with competition and the availability of new technology from fintech firms, South African banks have either strengthened their strategic cooperation with fintech firms or increased their investment in fintech (Genesis Analytics 2019). The growth of fintech benefits incumbent financial institutions through the development of emerging technologies in internet finance, such as third-party payment and peer-to-peer lending platforms, which can reduce banks’ transaction costs and improve risk management. These outcomes lead to reduced bankruptcy risk (increase in the Z-score) and increased banking systems stability. This positive effect of fintech on bank risk-taking is consistent with the findings of Pierri and Timmer (2020) and Haddad and Hornuf (2021). The nonlinear relationship implies that as fintech firms grow – or as banks increase their investment in fintech development – competition increases, which can adversely affect the stability of banks. Thus, beyond a certain level, more fintech development is associated with reduced stability of banks. The finding of a nonlinear (U-shaped) relationship between fintech development and risk-taking is consistent with that of Shen and Guo (2015) and Deng et al. (2021), who find that the impact of the development of internet finance on banks' risk-taking exhibits a U-shaped trend. The results are also consistent with those of Bakker et al. (2023), who document a nonlinear effect of fintech on gender and income inequality in Latin American countries.

Table 2: Effects of fintech formation on bank risk

Panel A: Fintech and default risk

	Contemporaneous				**Lag effects**	
	Linear effects		**Nonlinear effects**		**Nonlinear effects**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variable	Z-score	Ln Z-score	Z-score	Ln Z-score	Z-score	Ln Z-score
# Fintech	29.8001**	0.298487	97.67307**	4.232813***	25.39344	3.093526**
	(2.72)	(0.79)	(2.326)	(5.693)	(1.101)	(2.909)
# Fintech squared			-9.211579*	-0.539407***	-3.678475	-0.469606***
			(-1.802)	(-4.673)	(-1.210)	(-4.072)
$RISK_{(t-1)}$	0.1652***	0.479063***	0.171395***	0.511036***	0.212331**	1.145826***
	(3.04)	(4.25)	(3.165)	(3.977)	(2.716)	(6.781)
Size	-27.6780*	-0.246493	-33.25222**	-0.447132	15.53281**	0.121765
	(-2.02)	(-0.75)	(-2.219)	(-1.459)	(2.130)	(0.188)
Capital ratio	-0.905789	0.001104	-0.740001	-0.015595	1.691356	-0.043733
	(1.27)	(0.05)	(-0.564)	(-0.510)	(1.302)	(-0.905)
Interest income share	-3.857502	-0.167872	-2.382278	-0.091997	-0.516375	0.148607
	(-1.010926)	(-1.52)	(-0.647)	(-0.613)	(-0.627)	(1.567)
Debt equity ratio	-18.2628**	-0.645841***	-19.37274***	-0.723918***	-9.360273	-0.451085
	(-2.81)	(-3.10)	(-2.938)	(-3.095)	(-2.360)	(-4.250)
Net income growth	-0.589285	-0.028648	-0.027489	-0.015651	-0.371874	-0.062807
	(-0.43)	(-1.09)	(-0.015)	(-0.562)	(-1.090)	(-1.238)
Inflation	2.1200**	0.078525***	1.409177	0.037275	-0.459496	-0.036827
	(2.14)	(3.04)	(1.456)	(1.237)	(-0.466)	(-0.718)
GDP growth	0.002239	0.000117**	0.00116	8.43E-06	-0.001725**	9.07E-05
	(1.48)	(2.87)	(0.675)	(0.159)	(-2.437)	(1.160)
SE of regression	31.28865	0.786971	32.40253	0.813293	27.2121	0.764426
Prob (J-statistic)	0.323789	0.170399	0.313126	0.132478	0.129629	0.336841
Observations	167	187	206	199	194	199
Instrument rank	17	17	17	17	17	16
Wald test: F	54.97177	43.55299	30.74738	73.48855	263.2174	35.54063
Wald test: chi-squared	494.7459	391.9769	307.4738	734.8855	2632.174	355.4063

Note: This table reports regression results of fintech formation on bank risk. Columns 1 and 2 show the contemporaneous linear model results, while columns 3 and 4 present the nonlinear model results. Columns 5 and 6 present the regression results using the lag of fintech formation as the primary independent variable. In these regressions, the dependent variable, RISK, represents the Z-score and Ln Z-score. The estimation method is the two-step GMM system dynamic panel estimator; p-values are based on heteroscedasticity-robust standard errors clustered at the bank level. T-statistics appear in parentheses, and the symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5.2.2 Lag effects of fintech formation on bank risk

Columns 1-4 of Table 2 indicate that fintech formation is associated with lower bankruptcy risk. These results suggest a contemporaneous relationship between bank solvency risk and fintech formation. Since fintech formation occurs throughout the year and newly formed firms may not impact incumbent firms' operations at the same time, it is reasonable to expect that the impact of fintech formations on bank risk will occur with a lag. In this section, we test whether fintech 'predicts' bank risk by re-estimating our baseline model using the lag of fintech as our primary independent variable and present the predictive model results in columns 5 and 6 of Table 2.[4]

The number of fintech startup formations positively predicts incumbent banks' default risk. The coefficient of the lag of fintech is positive in the regressions using both measures of the Z-score but is significant only in the Ln Z-score regression (coefficient of 3.09, t-statistics = 2.91). This result is consistent with that of Haddad and Hornuf (2021), who find that financial institutions' exposure to systemic risk decreases as more fintech firms enter the market. Overall, the results imply that fintech formations are not only associated with lower risk, but may also reduce the risk of default for South African banks. The control variables have the expected signs. The coefficient of Ln asset is mostly negative and significant, suggesting that larger banks generally exhibit higher default risk (lower Z-score), and higher leverage accentuates banks' default risk. The probability values of the Sargan tests of over-identifying restrictions imply that we cannot reject the null hypothesis that the instruments are valid.

5.3 Channels of risk reduction: profitability (ROA), equity-to-total-assets ratio (E/TA) and asset return volatility (σ_{ROA})

Our results suggest that incumbent banks experience less risk due to fintech development. Given the components of the Z-score, the risk reduction can emanate from improvements in profitability (ROA), an increase in the equity-to-total-assets ratio (E/TA) or a reduction in profit variability. A higher ROA and equity-to-total-assets ratio will lead to a reduction in bankruptcy risk, whereas higher profit variability leads to an

4 Here, some caution in interpreting the results is warranted. These 'predictive' results do not have a full *causal* interpretation as there may be some endogeneity.

increase in bankruptcy risk. Studies show that information technology is conducive to reducing banks' transaction costs and improving service quality (Martín-Oliver and Salas-Fumás 2008). Improvement in profitability can enhance the equity-to-total-assets ratio and reduce earnings variability (σ_{ROA}). On the other hand, increased competition and the perceived vulnerability of industry incumbents facing disruption from big tech firms' platforms can induce higher risk-taking by banks, causing greater variability in bank's profit margins (σ_{ROA}).

We examine the source of the reduction in risk by re-estimating equation 2 using ROA, E/TA as well as volatility of ROA as the dependent variable and present the results in Table 3. We find that fintech formation is positively related to all three components of the Z-score. Fintech formation strongly improves the profitability of banks, which also reflects in their equity-to-assets ratio. Although fintech development accentuates the profit variability of banks, the improvement in profitability and equity position outweighs the increase in profit variability. Thus, the risk reduction documented for the banks emanates from profitability and equity-to-assets ratio improvement. These results are consistent with the findings of prior studies, including Haddad and Hornuf (2021), which document significant positive effects of fintech formation on the profitability of financial institutions.

Table 3: Fintech and bank risk: channels

	ROA	SD of ROA	Equity-to-assets ratio
# Fintech	13.70908**	3.161669**	3.89277*
	(2.080)	(2.090)	(1.916)
# Fintech squared	-1.747098*	-0.155274	-0.614739**
	(-1.799)	(-0.773)	(-2.243)
Dep var$_{(t-1)}$	-0.05564	0.645007***	0.148476
	(-0.977)	(13.411)	(0.996)
Log of total assets	-1.789466***	-2.430663***	0.718133
	(-3.216)	(-4.401)	(1.498)
Capital ratio (or price-to-book ratio)	0.318756***	0.141774***	0.986127***
	(7.478)	(3.115)	(13.766)
Interest income share	0.103751	0.011785	0.06229
	(0.691)	(0.465)	(0.285)
Debt to equity	-2.568092***	0.757807**	0.11784
	(-7.480)	(2.697)	(0.132)
Net income growth	-0.109621	0.064243	0.325661
	(-0.385)	(1.200)	(0.792)
Inflation	0.004624	-0.023201	-0.054052
	(0.017)	(-0.299)	(-1.387)
GDP growth	-0.000492	2.97E-05	-0.000259**
	(-1.107)	(0.315)	(-2.666)
SE of regression	8.116383	3.961039	2.013945
Prob (J-statistic)	0.490062	0.210966	0.847432
Observations	221	206	223
Instrument rank	18	17	18
Wald test: chi-squared	31 503.88	25 2519.3	3 879 893

Note: This table reports regression results of fintech on the default risk of banks using the components of Z-score, namely ROA, standard deviation of ROA and equity-to-assets ratio. The estimation method is the two-step GMM system dynamic panel estimator. P-values are based on heteroscedasticity-robust standard errors clustered at the bank level. T-statistics appear in parentheses, and the symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5.4 Is the effect of fintech formation on bank risk dependent on the size of incumbents?

Next, we test whether the effects of fintech startup formations on banks in South Africa differ based on size. Prior research (such as Talavera, Yin and Zhang 2018; Phan et al. 2020) suggests that financial institution characteristics, such as size, are significant predictors of performance. Large universal institutions might benefit from alliances with fintech companies, which could help them obtain specialised knowledge and improve their performance through product-related cooperation (Hornuf et al. 2021). This means that they can reduce their risk more than small banks. In addition, large financial institutions often have the financial wherewithal to pursue change through acquisitions and in-house experimentation to compete with fintech firms.

On the other hand, smaller banks are more agile, can adapt quickly to changes and might benefit more from alliances with fintech firms. Moreover, smaller, more specialised financial institutions might possess more modern information technology infrastructure and therefore benefit more from fintech formations. As a result, we expect that fintech firms will affect large and small banks differently. Using total assets as a proxy for size, we split the sample into large and small banks. Firms with total assets higher than the median are classified as large banks and those with total assets less than the median are considered small banks. We then estimate our main regression separately for the two groups to determine whether fintech startups have a differential impact on incumbent banks' risk. To ascertain whether this potential heterogeneity could account for the nonlinearity we observed earlier, we include $fintech^2$ in both regressions.

The results, presented in Table 4, are noteworthy, showing that fintech formation has heterogeneous effects on large and small banks. Panel A, which contains the contemporaneous and predictive effects of fintech formations on the bankruptcy risk of large banks, indicates a negative and significant association between fintech formations and the bankruptcy risk of large banks. This suggests that fintech development makes large banks more unstable. The lag regression results in columns 3 and 4 show that fintech formations predict the default risk of large banks in South Africa. However, the results presented in Panel B show that fintech formations positively predict improvement in the bankruptcy risk of smaller banks. Another striking result is that the nonlinear relationship documented earlier in this paper is more related to large banks because the coefficient of $fintech^2$ is significant in all four regressions for large banks, whereas the nonlinear relation is weak for small banks.

Overall, fintech formations appear to adversely affect large banks' bankruptcy risk and positively affect small banks. These results are consistent with the argument that smaller banks benefit more from fintech formations (Haddad and Hornuf 2021). The results are also consistent with the conjecture that large banks are slow in adopting and using technological innovations due to bureaucratic cultures compared to small banks, which may adopt innovations proactively (Phan et al. 2020). Large firms respond slowly to technological transformations due to their legacy systems, which may require substantial modifications. Consequently, they must bear substantially higher costs in reorganising their infrastructure than smaller firms, which can adjust more easily (Scott, van Reenen and Zachariadis 2017).

Table 4: Differential effects of fintech on large and small banks

Panel A: Effect of fintech formation on large banks

Contemporaneous effects				Lag effects		
Variable	**Z-score**	**Ln Z**		**Variable**	**Z-score**	**Ln Z**
# Fintech	-1 279.11***	-57.992**		# $Fintech_{(t-1)}$	-518.997***	-21.1079*
	(-5.624)	(-2.513)			(-5.417)	(-2.141)
# Fintech squared	179.7627***	7.8726**		# $Fintech_{(t-1)}$ squared	69.8116***	2.5035*
	(5.643)	(2.462)			(4.935)	(1.852)
Controls	Yes	Yes		Controls	Yes	Yes
Observations	156	156		Observations	156	156
Prob (J-statistic)	0.284	0.218		Hansen	0.290281	0.215975
Wald test: F	460.848	3 126.818		Wald test: F	308.0554	1 839.585

Panel B: Effect of fintech formation on small banks

Contemporaneous effects				Lag effects		
# Fintech	244.9274*	8.1647**		# $Fintech_{(t-1)}$	289.8463*	8.4168*
	(2.007)	(2.418)			(1.825)	(2.204)
# Fintech squared	-31.9246*	-1.1461*		# $Fintech_{(t-1)}$ squared	-40.325*	-1.2586*
	(-1.720)	(-1.811)			(-1.687)	(-1.940)
Controls	Yes	Yes		Controls	Yes	Yes
Observations	62	62		Observations	62	62
Prob (J-statistic)	0.581321	0.139619		Prob (J-statistic)	0.5131	0.231647
Wald test: F	323.5693	1530		Wald test: F	8 631.797	785.4445

Note: This table reports regression results of the impact of fintech formations on large and small banks using two versions of the dependent variable, Z-score and Ln Z-score. Large banks are those with total assets more than the median bank's, and small banks are those with total assets less than that of the median bank. The estimation method is the two-step GMM system dynamic panel estimator. We do not report the control variables for brevity's sake. P-values are based on heteroscedasticity-robust standard errors clustered at the bank level. T-statistics appear in parentheses, and the symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5.5 Fintech and default risk of non-bank financial institutions and the financial sector

The focus of the analysis thus far has been on banks, the key players in the financial system of South Africa. In this section, we examine whether fintech formations affect the risk of non-bank financial institutions (such as insurance companies and wealth management funds). We use the same measure of default risk, that is, the Z-score and control variables, except that we replace banks' interest income with the cost-to-income ratio because the former is not common for non-bank financial institutions. The results are presented in Table 5. Panel A shows the contemporaneous and lag effects of fintech formations on non-bank financial institutions' default risk, and Panel B presents similar results for the whole financial sector.

Consistent with the results presented in Table 2 for banks, fintech formations positively affect the Z-score of non-bank financial institutions, suggesting that fintech formations lead to a lower default risk for non-bank financial institutions. The results for the combined sample in columns 3 and 4 of Table 5 are similar: fintech firms make South Africa's financial system more stable.[5] The magnitude of the effects on non-bank financial institutions is smaller than that on banks reported in Table 2.

[5] The results based on the Ln Z-score are similar and therefore are not reported here for brevity.

Table 5: Fintech formation and default risk of non-bank financial institutions and the full sample

	Non-bank financial institutions		Full sample	
Variable	Contemporaneous	Lag	Contemporaneous	Lag
# Fintech	18.63476***	12.48963***	25.4965***	17.0485***
	(3.658)	(3.099)	(7.263)	(5.476)
# Fintech squared	-1.518978*	-0.963634	-1.9144***	-0.8784***
	(-1.519)	(-1.434)	(-4.232)	(-2.319)
$RISK_{(t-1)}$	0.160469***	0.163597***	0.1251***	0.121704***
	(21.405)	(7.184)	(55.076)	(26.030)
Log of total assets	-8.12996***	-0.263556	-0.9664***	1.323945***
	(-9.333)	(-0.511)	(-5.234)	(2.883)
Capital ratio	0.018116	0.121117	0.1625***	0.1528***
	(0.752)	(1.586)	(15.454)	(8.120)
Cost to income	-0.185426	-0.080596**	0.0814***	0.1079***
	(-1.574)	(-2.119)	(8.831)	(3.978)
Price to book	2.465039***	0.410215*	1.0651***	1.1983***
	(2.773)	(1.642)	(11.693)	(7.062)
Net income growth	0.040765	0.136164	0.4813***	0.4330***
	(0.503)	(0.639)	(9.543)	(7.445)
Inflation	-0.45348***	-0.556439***	-0.1532***	0.1315***
	(-4.766)	(-7.710)	(-4.683)	(4.281)
GDP growth	-0.000956***	-0.001508***	-0.0021***	-0.0021***
	(-2.918)	(-4.002)	(-9.982)	(-8.974)
SE of regression	22.72832	20.2807	23.67592	24.3986
Prob (J-statistic)	0.405075	0.415691	0.417028	0.3672
Observations	357	337	528	528
Instrument rank	41	40	53	54
Wald test: chi-squared	15 123.33	691.5258	19 458.64	3 713.241

Note: This table contains regression results showing the impact of fintech formations on the default risk (Z-score) of non-bank financial institutions and the whole sample. The estimation method is the two-step GMM system dynamic panel estimator. P-values are based on heteroscedasticity-robust standard errors clustered at the firm level. T-statistics appear in parentheses, and the symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5.6 Fintech development and performance of banks and non-bank financial institutions

We also examine the effect of fintech development on the performance of financial institutions. As discussed, the impact of fintech formations on financial institutions' performance is unclear. On the one hand, fintech firms, which develop and apply innovative technology to perform tasks previously reserved for banks such as lending, payments, or investments, can substitute for traditional banks as they provide less expensive and more efficient services (Phan et al. 2020). This suggests that the growth of fintech firms can negatively influence bank performance. On the other hand, fintech firms' innovative products and services can lead to more cooperation, which can benefit financial institutions. Previous research (such as Vives 2019) posits that financial institutions rethink and reshape their business models when confronted with competitive pressures. One potential way they can improve performance is to cooperate with and integrate the new players into their organisation (Hornuf et al. 2020). This cooperation can benefit financial institutions through the application of innovative technology and better risk management tools developed by fintech firms, which could lead to performance improvements.

In this section, we investigate the effects of fintech formations on the performance of incumbent financial institutions and present the results in Table 6. In these regressions, we use the lag of fintech as the independent variable. The results indicate that fintech formation significantly predicts improvements in the ROA, stock returns and Tobin's Q of financial institutions in South Africa.[6] The coefficient of fintech is consistently positive and significant at the 1% level. The stock return results are similar to those of Li, Spigt and Swinkels (2017), who examined the impact of fintech on bank stock prices and found a positive correlation between the growth of fintech firms and banks' stock returns. Consistent with our earlier results on default risk and prior studies (such as Bakker et al. 2023), the relationship between fintech formations and the operating performance of incumbent financial institutions is nonlinear.

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6 Again, we caution that these 'predictive' results do not have a full *causal* interpretation.

Table 6: Effects of fintech firms on the performance of financial institutions

Variable	ROA	Stock returns	Tobin's Q
# Fintech$_{(t-1)}$	66.24733***	826.1255***	4.51389***
	(9.378)	(10.425)	(52.553)
# Fintech$_{(t-1)}$ squared	-8.209302***	-116.1982***	0.159836***
	(-7.798)	(-10.045)	(10.509)
PERFORMANCE$_{(t-1)}$	-0.143103***	-0.205545***	0.726831***
	(-17.903)	(-94.076)	(5 475.627)
Log of total assets	-29.07815***	-82.89494***	-4.60474***
	(-30.634)	(-37.997)	(-1 952.669)
Capital ratio	0.545061***	1.27312***	-0.020063***
	(20.964)	(15.904)	(-62.351)
Cost to income	1.143507***	2.514358***	0.025733***
	(6.245)	(16.487)	(6.204)
Price to book	-9.896555***	-32.42622***	-0.311108***
	(-17.862)	(-79.381)	(-211.203)
Net income growth	5.213044***	13.47029***	0.083832***
	(28.458)	(20.586)	(116.020)
Inflation	0.720385**	-0.596613	0.223916***
	(1.888)	(-0.640)	(273.237)
GDP growth	-0.00499***	-0.00689	0.000341***
	(-8.585)	(-1.581)	(46.643)
SE of regression	52.65496	162.3204	12.13097
Prob (J-statistic)	0.387674	0.568	0.269793
Observations	557	426	576
Instrument rank	42	36	55
Wald test: chi-squared	200 899.9	578 463.8	1.93E+10

Note: This table reports the results of the regressions showing the impact of fintech formation on financial institutions' performance. Performance represents one of the three dependent variables: ROA, stock returns and Tobin's Q. The estimation method is the two-step GMM system dynamic panel estimator. P-values are based on the heteroscedasticity-robust standard errors clustered at the firm level. T-statistics appear in parentheses, and the symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5.7 Fintech and financial institution stability: country-level analysis

The analysis thus far is based on firm-level data, which helps demonstrate firm heterogeneity within a sector or a country. Since the focus is on South Africa, the results may be difficult to generalise to other countries because of differences in the reporting system underlying the data or methodology used to compile the data. For generalisation purposes, the data used must be compiled using the same methodology for different countries. We obtain country-level data on bankruptcy risk and other related variables from the Global Financial Development Database, which allows us to estimate the effect of fintech on financial stability using aggregate data. This database is an extensive dataset of financial system characteristics for 214 countries. It contains annual data on the stability of financial systems, specifically the aggregate (country-level) Z-score, NPLs, bank interest margin and the cost-to-income ratio, among others.

The database draws on a common analytical framework and definition of standard methodologies to compile the data, which allows for cross-country comparisons and generalisation of the results. Using these aggregate data, we re-estimate our primary regression and report the results in Table 7.[7]

Table 7: Country-level analysis of the effect of fintech on financial institution stability

Contemporaneous effects of fintech				Predictive effects of fintech		
	(1)	(2)			(3)	(*4)
Variable	Bank Z-score	Ln bank Z-score		Variable	Bank Z-score	Ln bank Z-score
# Fintech	2.40236*	0.162932**		# Fintech$_{(t-1)}$	2.588482*	0.177609*
	(2.2889)	(2.473)			(2.011)	(2.188)
RISK$_{(t-1)}$	-0.221119	-0.248894		RISK$_{(t-1)}$	-0.295742	-0.332991
	(-0.645)	(-0.750)			(-0.746)	(-0.864)
ATM	0.028013	0.002341		ATM	0.041571	0.003358
	(0.798)	(1.009)			(1.082)	(1.296)
Domestic credit	-0.280749	-0.013786		Domestic credit	-0.167565	-0.005489
	(-0.823)	(-0.635)			(-0.486)	(-0.247)
Bank branches	0.722423*	0.051133*		Bank branches	0.749156*	0.053315*
	(1.956)	(2.137)			(1.962)	(2.105)
Regulatory capital	-0.061651	-0.004198		Regulatory capital	-0.036655	-0.00238
	(-0.258)	(-0.276)			(-0.146)	(-0.149)
Outstanding deposits	-0.113987	-0.008227		Outstanding deposits	-0.037471	-0.002723
	(-0.745)	(-0.866)			(-0.200)	(-0.231)
Inflation	19.30353	1.494984		Inflation	24.71469	1.925252
	(0.857)	(0.970)			(0.988)	(1.111)
GDP growth	2.40236*	0.162932**		GDP growth	2.588482*	0.177609*
	(2.289)	(2.473)			(2.011)	(2.188)
C	0.170681	1.998968*		C	-3.996627	1.826822**
	(0.011)	(2.312)			(-0.255)	(2.049)
Adjusted R-squared	0.851878	0.875403		Adjusted R-squared	0.834241	0.860066
SE of regression	0.668958	0.041552		SE of regression	0.707665	0.044035
Observations	15	15		Observations	15	15
F-statistic	11.06457	13.29531		F-statistic	9.807476	11.75591
Durbin-Watson stat	2.010611	2.138575		Durbin-Watson stat	1.865553	1.945784

Note: This table presents regression results of the effect of fintech formation on financial institutions using aggregate (country-level) data. The estimation method is ordinary least squares. P-values are based on heteroscedasticity-robust standard errors. T-statistics appear in parentheses, and the symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

[7] For this analysis, we use only the South African data from this database, which explains why there are only 15 observations.

The results in columns 1 and 2 show the contemporaneous effects of fintech formation on the stability of financial institutions, while those in columns 3 and 4 show the 'predictive' effects of fintech. Consistent with the firm-level results, fintech formation positively affects the aggregate Z-score.[8] Similar and consistent results are obtained when we use the Ln Z-score as our measure of bankruptcy risk. In columns 3 and 4, we report the results using the lag of fintech startup formations for the country-level default risk regression. We find that the lag of fintech startup formations is positively and significantly related to the country-level aggregate bank Z-score, suggesting that, on average, fintech development improves financial system stability in South Africa. These results are consistent with the firm-level results documented in Table 2.

5.8 Robustness test

5.8.1 Controlling for the effects of the global financial crisis

To ascertain the robustness of our results, we carry out four additional tests. First, in the analysis thus far, we do not control for the effects of the global financial crisis (GFC), which could confound our results. In this section, we re-estimate our primary regression while controlling for the effects of the crisis by including in the regression a GFC dummy defined as 1 for the 2007–2008 period and 0 otherwise. The results of the augmented model presented in Table 8 are similar to our previous findings – fintech formation is associated with lower default risk for banks and other financial institutions in South Africa. Regarding performance, we find that fintech startup formations are positively associated with financial institutions' performance, as shown by the increase in ROA, stock return and Tobin's Q, even after controlling for the effect of the GFC. The coefficients of the control variables are not reported here for brevity's sake.

We also examine whether financial institutions' default risk and performance have changed in the aftermath of the GFC. To ascertain this, we introduce a post-GFC dummy that takes a value of 1 for the period after 2007–2008 and 0 before the crisis and present the results in Panel B.[9] The coefficient of the post-GFC dummy is significantly positive, suggesting that the risk of financial institutions has reduced in the

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8 The squared term is excluded from the regression since its inclusion reduces both the R-squared and adjusted R-squared.

9 We exclude 2007 and 2008 from the analysis because of possible confounding effects.

period after the financial crisis. These results could be attributed to the enhanced regulatory regime following the implementation of Basel III regulations in the post-GFC period. The profitability (ROA) and firm value (Tobin's Q) have improved, but the stock returns are significantly lower in the post-crisis period.

Table 8: Robustness tests: controlling for the effects of the GFC

Panel A: Effects of the GFC

Bankruptcy risk				Performance		
Variable	**Z-score**	**Ln Z-score**		**ROA**	**Stock returns**	**Tobin's Q**
# Fintech$_{(t-1)}$	46.89247***	0.762862***		31.9985***	669.7196***	4.196119***
	(2.811)	(5.223)		(8.247)	(27.257)	(25.699)
# Fintech$_{(t-1)}$ squared	-6.793309***	-0.101748***		-1.420932***	-83.08382***	0.184276***
	(-2.793)	(-4.688)		(-2.717)	(-25.611)	(7.247)
Dep var$_{(t-1)}$	0.829791***	0.281393***		-0.146479***	-0.147931***	0.727002***
	(17.244)	(8.120)		(-75.064)	(-37.605)	(3968.244)
GFC	1.915352	-0.212033***		7.695369***	49.20022***	-1.526317***
	(0.555)	(-3.482)		(15.687)	(12.007)	(-46.631)
Controls	Yes	Yes		Yes	Yes	Yes
Observations	548	517		587	426	576

Panel B: Recency effects: post-GFC effects

Variable	**Z-score**	**Ln Z-score**		**ROA**	**Stock returns**	**Tobin's Q**
# Fintech$_{(t-1)}$	40.58422**	0.623897***		65.6579***	731.8842***	3.2936***
	(2.466)	(5.415)		(10.541)	(22.580)	(8.692)
# Fintech$_{(t-1)}$ squared	-5.91287**	-0.092178***		-8.510091***	-89.63126***	1.001986***
	(-2.424)	(-4.879)		(-9.567)	(-20.778)	(20.449)
Dep var$_{(t-1)}$	0.812593***	0.269369***		-0.143932***	-0.152652***	0.643764***
	(15.482)	(10.368)		(-25.334)	(-33.008)	(3 441.573)
Post-GFC	2.376532	0.412573***		6.397676**	-57.13942***	5.562518***
	(0.501)	(5.400)		(2.118)	(-7.599)	(27.160)
Controls	Yes	Yes		Yes	Yes	Yes
Observations	548	517		587	426	576

Note: Panel A shows the effects of fintech formation on financial institutions' risk and performance while controlling for the effects of the GFC. The crisis is captured by a GFC dummy that takes a value of 1 for the years 2007 and 2008 and 0 otherwise. Panel B presents the results of the regressions that show whether the effects of fintech have changed after the GFC. The post-GFC dummy takes a value of 1 for the period after 2007 and 2008 and 0 before the financial crisis. Risk is measured using the Z-score and Ln Z-score, and performance represents one of three dependent variables: ROA, stock returns and Tobin's Q. The estimation method is the two-step GMM system dynamic panel estimator. P-values are based on heteroscedasticity-robust standard errors clustered at the firm level. T-statistics appear in parentheses, and the symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5.8.2 Alternative measure of Z-score

Our main measure of bankruptcy risk, the Z-score, consists of three components: ROA, the equity-to-assets ratio and standard deviation of ROA. In estimating the Z-score, we use a three-year moving average to estimate the volatility of ROA. The rolling average method involves dropping the earliest observations each time. Moreno, Parrado-Martínez and Trujillo-Ponce (2021) estimate and compare the explanatory power of six different measures of the Z-score and find that the best measure that incorporates the most statistically significant variables in the risk model is the one that uses the standard deviation of ROA calculated over the entire period. The advantage of this Z-score is that it enables the construction of time-varying Z-scores that do not require initial observations to be dropped (Moreno, Parrado-Martínez and Trujillo-Ponce 2021). To ascertain whether our results depend on how we estimate our key risk measure, we employ the Z-score proposed by Moreno, Parrado-Martínez and Trujillo-Ponce (2021), which uses the standard deviation of ROA calculated over the entire period. Beck and Laeven (2006) also use this Z-score in their study. The results of this alternative measure are presented in Table 9, columns 1 and 2. Consistent with the main findings, the coefficient of fintech is positive and significant, confirming our earlier results that fintech formations are positively associated with financial institutions' stability. The other explanatory variables remain qualitatively the same.

Table 9: Robustness tests: alternative measures of risk

Panel A: Results based on Z-score and NPL

	Z-all (full sample)		**NPL (banks)**	
Variable	**Contemporaneous effect**	**Lag effect**	**Contemporaneous effect**	**Lag effect**
# Fintech	16.87864***	9.688636***	-9.215497*	-6.650445
	(11.776)	(8.175)	(-1.763)	-(1.378)
# Fintech squared	-1.86263***	-1.02089***	1.182619*	0.914954*
	(-10.245)	(-6.029)	(1.73)	(1.646)
$RISK_{(t-1)}$/ $Performance_{(t-1)}$	0.161981***	0.16308***	0.429195*	0.378454*
	(148.604)	(167.467)	(1.712)	(2.038)
Log of total assets	-10.15934***	-8.75901***	2.008316	1.177561
	(-33.395)	(-37.481)	(1.605)	(0.705)
Capital ratio	0.134563***	0.162206***	0.267101	0.284915
	(24.728)	(12.161)	(0.915)	(1.507)
Interest income/CTI	0.00714	0.029559	-0.917347	-6.255041
	(0.248)	(0.741)	(-0.063)	(-0.794)
Price to book	1.842856***	1.713321***	2.093151*	1.804564*
	(26.002)	(22.624)	(1.710)	(2.0501)
Net income growth	-0.071653	-0.13083**	-0.721022*	-0.61129*
	(-1.511)	(-2.352)	(-1.912)	(-1.789)
Inflation	0.32293***	0.475332***	0.293317*	0.177647
	(13.299)	(17.515)	(2.035)	(1.599)
GDP growth	0.000141***	0.000392**	0.000245	0.000153
	(4.659)	(10.932)	(1.361)	(0.877)
Observations	548	548	137	137

Panel B: Market-based measures of risk-stock return volatility

	Banks		Non-bank financial institutions		Full sample	
Variable	**Contemp. effect**	**Lag effect**	**Contemp. effect**	**Lag effect**	**Contemp. effect**	**Lag effect**
# Fintech	0.591687	41.58807	-68.99302***	-34.938***	-50.008***	-34.516***
	(0.617)	(0.632)	(-5.561)	(-10.031)	(-14.109)	(-33.916)
# Fintech squared	-10.30708	-4.271861	10.38685***	6.24456***	7.69105***	5.751895***
	(-0.637)	(-0.513)	(5.925)	(9.802)	(15.180)	(34.244)
$RISK_{(t-1)}$	0.591687	0.638511	0.194841***	0.19514***	0.182512***	0.180507***
	(0.617)	(0.668)	(23.198)	(19.073)	(46.351)	(55.930)
Log of total assets	-21.7197	-17.64912	-2.334381***	-5.0079***	-3.690085***	-3.962466***
	(-1.111)	(-1.398)	(-2.790)	(-3.986)	(-7.509)	(-8.449)
Capital ratio	-2.325359*	-2.12256**	0.164073***	0.19345***	0.209618***	0.223307***
	(-1.901)	(-2.836)	(24.864)	(19.062)	(47.131)	(42.485)
Interest income/CTI	-0.287552	-1.521177	0.065717	0.072998	-0.102858***	-0.09202***
	(-0.032)	(-0.245)	(1.265)	(1.352)	(-10.978)	(-6.360)
Price to book	1.447139	-1.541645	1.072818***	0.9929***	-0.148611***	-0.161689**
	(0.065)	(-0.096)	(9.908)	(8.650)	(-4.776)	(-2.595)
Net income growth	1.121854	0.435061	-1.155179***	-1.0321***	-1.46786***	-1.957403***
	(0.675)	(0.791)	(-5.711)	(-6.389)	(-35.087)	(-37.197)
Inflation	0.482802	1.446124	1.590002***	1.33403***	1.369***	1.227248***
	(0.544)	(0.900)	(12.855)	(9.840)	(23.906)	(25.233)
GDP growth	-0.000416	0.000786	0.001505*	0.000562	0.001009***	0.000495***
	(-0.120)	(0.366)	(0.064)	(0.986)	(3.677)	(3.659)
Observations	187	186	367	367	564	563

Note: This table presents the results of the regressions of alternative measures of risk on the fintech formation variable and the control variables. Panel A shows the results of alternative accounting-based risk measures (NPLs and an alternative measure of the Z-score), while Panel B presents the results of the market-based risk measure (stock returns volatility). P-values are based on the heteroscedasticity-robust standard errors clustered at the firm level. T-statistics appear in parentheses, and the symbols *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5.8.3 Alternative measure of bank risk: non-performing loans

Ari, Chen and Ratnovski (2019) show that NPLs can affect the probability of a systemic crisis in the banking sector when distressed assets exceed 7% of total bank assets. To provide further robustness, we re-estimate our baseline regression using the ratio of NPLs to gross loans as an alternative accounting-based measure of risk. The results are presented in Table 9 (columns 3 and 4). Consistent with our previous findings based on the Z-score, the contemporaneous and 'predictive' regressions show that fintech development is associated with lower NPLs and therefore lower risk. The rest of the results are consistent with our previous findings based on the Z-score.

5.8.4 Market-based measure of risk: stock return volatility

Our key measure of risk, the Z-score, is based mainly on historical accounting data and may not accurately reflect the actual conditions of a financial institution. Moreover, if financial institutions can smooth out their reported earnings, the Z-score will provide an overly optimistic assessment of the financial institution’s insolvency risk (Laeven and Majnoni 2003; Haddad and Hornuf 2021). In addition, existing literature asserts that changes in risk could be driven by changes in market expectations regarding future profitability, returns or growth opportunities (Mohsni and Otchere 2014). Therefore, to obtain further insights into the influence of fintech development on financial institutions’ risk, we use market-based proxies of risk, namely stock return volatility, in our baseline regression as an alternative measure of risk and report the results in Panel B of Table 9. Similar to the risk reduction results documented using accounting-based measures of risk (the Z-score and NPL), we find that the coefficient of fintech is mostly negative and significant, implying a reduction in stock return volatility of non-bank financial institutions and the whole sample. In summary, our results are robust to using different measures of risk, different data types and different estimation methods, and to controlling for the effects of the GFC.

6. Summary and conclusion

In this study we examine the effects of fintech startup formations on the stability and performance of financial institutions in South Africa – a country that has experienced significant growth in fintech firms in recent decades. We find evidence that fintech formations help reduce financial institutions’ default risk and improve their operating performance overall. Consistent with previous research, we also document the existence of a nonlinear relationship between fintech formation and the risk of financial institutions in South Africa. This suggests that initial collaboration between fintech firms and incumbent financial institutions later tends to intensify competition as the fintech sector grows, resulting in increased risk-taking (Wang, Liu and Luo 2021). We also find that the effects of fintech formation are heterogeneous for banks, as large banks experience an increase in default risk, while small banks experience less systemic risk with fintech development.

Our study has important implications for managers and regulators. First, from a financial institution’s perspective, partnering with fintech firms to provide technological capabilities would benefit incumbent institutions. Second, the finding that fintech formation is negatively associated with large banks' risk calls for caution on the part of policymakers, as fintech development can accentuate the 'too big to fail' problem. In addition, collaboration between banks and fintech firms can create stability problems. The risks stemming from the failure of fintech firms or data breaches could affect the whole financial system because of the interconnectedness that results from such partnerships.

Our study suffers from data limitations. Although prior studies have also used the number of fintech firms (see Phan et al. 2020 and Haddad and Hornuf 2021), it should be noted that fintech firms are always at different stages of development and are, therefore, likely to impact incumbent financial institutions' risk-taking differently. It is inherently difficult to capture these potential heterogenous effects with the fintech data currently at our disposal (i.e. the number of fintech firms). Using this variable without any weighting to capture the heterogeneity implicitly assumes that early-stage fintech firms have the same impact on incumbents as the large and well-established ones. Second, although the fintech sector in South Africa is the most developed in Africa, the market is still evolving. As the fintech sector develops and becomes a significant part of the financial sector and a broader range of digital financial services (e.g. crypto-assets) emerges, the availability of granular and richer data would facilitate a deeper, holistic analysis of the impact of fintech development on the stability of the financial system.

References

Absa Bank Ltd. 2016. *Absa Bank Limited annual report 2016*.

Acar, O and Çitak, Y E. 2019. 'Fintech integration process suggestion for banks'. *Procedia Computer Science* 158: 971–978.

Anilowski, C, Feng, M and Skinner, D J. 2007. 'Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance'. *Journal of Accounting and Economics* 44(1–2): 36–63.

Arellano, M and Bover, O. 1995. 'Another look at the instrumental variable estimation of error components models'. *Journal of Econometrics* 68(1): 29–51.

Ari, A, Chen, S and Ratnovski, L. 2019. 'The dynamics of non-performing loans during banking crises: a new database'. IMF Working Papers No. 2019/272.

Arner, D, Barberis, J and Buckley, R. 2015. 'The evolution of fintech: a new post-crisis paradigm?' University of Hong Kong Faculty of Law Research Paper No. 2015/047.

Bains, P, Sugimoto, N and Wilson, C. 2022. 'BigTech in financial services: regulatory approaches and architecture'. IMF Fintech Notes 2022/002.

Bakker, B B, Garcia-Nunes, B, Lian, W, Liu, Y, Perez Marulanda, C, Siddiq, A, Sumlinski, M A, Vasilyev, D and Yang, Y. 2023. 'The rise and impact of fintech in Latin America'. IMF Fintech Notes 2023/03.

Baltagi, B. 2001. *Econometric analysis of panel data*. 2nd edition. Chichester: John Wiley and Sons.

Beck, T, Chen, T, Lin, C and Song, F M. 2016. 'Financial innovation: the bright and the dark sides'. *Journal of Banking & Finance* 72: 28–51.

Beck, T and Laeven, L. 2006. 'Resolution of failed banks by deposit insurers: cross-country evidence'. World Bank Policy Research Working Paper 3920.

Berger, A N. 1995. ‘The profit-structure relationship in banking – tests of market-power and efficient-structure hypotheses’. *Journal of Money, Credit and Banking* 27: 404–431.

Berger, A N and Bouwman, C H. 2017. ‘Bank liquidity creation, monetary policy, and financial crises’. *Journal of Financial Stability* 30: 139–155.

Bernstein, S, Korteweg, A and Laws, K. 2017. ‘Attracting early-stage investors: evidence from a randomized field experiment’. *The Journal of Finance* 72(2): 509–538.

Blundell, R and Bond, S. 1998. ‘Initial conditions and moment restrictions in dynamic panel data models’. *Journal of Econometrics* 87(1): 115–143.

Brandl, B and Hornuf, L. 2020. ‘Where did FinTechs come from, and where do they go? The transformation of the financial industry in Germany after digitalization’. *Frontiers in Artificial Intelligence* 3.

Chen, X, You, X and Chang, V. 2021. ‘FinTech and commercial banks’ performance in China: a leap forward or survival of the fittest?’ *Technology Forecasting and Social Change* 166: 120645.

Christensen, C. 1997. *The innovator’s dilemma: when new technologies cause great firms to fail*. Boston: Harvard Business School Press.

Coetzee, J. 2019. ‘Risk aversion and the adoption of fintech by South African banks’. *African Journal of Business and Economic Research* 14: 133–153.

Dapp, T. 2014. ‘Fintech – the digital (r)evolution in the financial sector’. Deutsche Bank Research.

Dapp, T. 2015. ‘Fintech reloaded – traditional banks as digital ecosystems’. Deutsche Bank Research.

Deloitte. 2017. ‘Fintechs and regulatory compliance: understanding risks and rewards’.

Demirgüç-Kunt, A and Huizinga, H. 1999. ‘Determinants of commercial bank interest margins and profitability: some international evidence’. *World Bank Economic Review* 13(2): 379–408.

Deng, L, Lv, Y, Liu, Y and Zhao, Y. 2021. ‘Impact of fintech on bank risk-taking: evidence from China’. *Risks* 9(5): 99.

Didier, T, Feyen, E, Llovet Montañés, R and Ardic, O. 2022. ‘Global patterns of fintech activity and enabling factors’. Fintech and the future of finance flagship technical note. Washington, DC: World Bank.

Dietrich, A and Wanzenried, G. 2014. ‘The determinants of commercial banking profitability in low-, middle- and high-income countries’. *The Quarterly Review of Economics and Finance* 54(3): 337–354.

Feyen, E, Natarajan, H and Saal, M. 2023. *Fintech and the future of finance: market and policy implications*. Washington, DC: World Bank.

FirstRand Group Ltd. 2017. *FirstRand annual integrated report 2017*.

Flamini, V, Schumacher, L and McDonald, C. 2009. ‘The determinants of commercial bank profitability in sub-Saharan Africa’. IMF Working Paper 09/15.

Genesis Analytics. 2019. *Fintech scoping in South Africa*.

Gupta, P T and Mandy, T. 2018. *Fintech: the new DNA of financial services*. De Gruyter.

Haddad, C and Hornuf, L. 2021. ‘The impact of fintech startups on financial institutions performance and default risk’. CESifo Working Paper No. 9050.

Hellman, T F, Murdock, K C and Stiglitz, J E. 2000. ‘Liberalization, moral hazard in banking, and prudential regulation: are capital requirements enough?’ *The American Economic Review* 90(1): 147–165.

Hornuf, L, Klus, M F, Lohwasser, T S and Schwienbacher, A. 2021. ‘How do banks interact with fintech startups?’ *Small Business Economics* 57: 1505–1526.

Houston, J F, Lin, C, Lin, P and Ma, Y. 2010. ‘Creditor rights, information sharing, and bank risk taking’. *Journal of Financial Economics* 96(3): 485–512.

IMF. 2022. ‘South Africa: Financial Sector Assessment Program – technical note on systematic liquidity management’. IMF eLibrary.
https://www.elibrary.imf.org/view/journals/002/2022/183/article-A001-en.xml

Jameaba, M. 2020. ‘Digitization revolution, fintech disruption, and financial stability: using the case of Indonesian banking ecosystem to highlight wide-ranging digitization opportunities and major challenges’.

Jiménez, G, Lopez, J A and Saurina, J. 2013. ‘How does competition affect bank risk-taking?’ *Journal of Financial Stability* 9(2): 185–195.

Keeley, M C. 1990. ‘Deposit insurance, risk, and market power in banking’. *American Economic Review* 5: 1183–1200.

Kommel, K A, Sillasoo, M and Lublóy, Á. 2019. ‘Could crowdsourced financial analysis replace the equity research by investment banks?’ *Finance Research Letters* 29: 280–284.

Laeven, L and Levine, R. 2009. ‘Bank governance, regulation and risk taking’. *Journal of Financial Economics* 93(2): 259–275.

Laeven, L and Majnoni, G. 2003. ‘Loan loss provisioning and economic slowdowns: too much, too late?’ *Journal of Financial Intermediation* 12(2): 178–197.

Laven, M and Bruggink, D. 2016. ‘How FinTech is transforming the way money moves around the world: an interview with Mike Laven’. *Journal of Payments Strategy & Systems* 10(1): 6–12.

Lepetit, L, Nys, E, Rous, P and Tarazi, A. 2008. ‘Bank income structure and risk: an empirical analysis of European banks’. *Journal of Banking & Finance* 32(8): 1452–1467.

Li, Y, Spigt, R and Swinkels, L. 2017. ‘The impact of FinTech start-ups on incumbent retail banks’ share prices’. *Financial Innovation* 3(26): 1–16.

Marcus, A J. 1984. ‘Deregulation and bank financial policy’. *Journal of Banking and Finance* 8(4): 557–565.

Martín-Oliver, A and Salas-Fumás, V. 2008. ‘The output and profit contribution of information technology and advertising investments in banks’. *Journal of Financial Intermediation* 17(2): 229–255.

Mohsni, S and Otchere, I. 2014. ‘Risk taking behavior of privatized banks’. *Journal of Corporate Finance* 29: 122–142.

Moreno, I, Parrado-Martínez, P and Trujillo-Ponce, A. 2021. ‘Using the Z-score to analyze the financial soundness of insurance firms’. *European Journal of Management and Business Economics* 31(1): 22–39.

Nedbank Group Ltd. 2016. *Integrated report 2016*.

Pathan, S. 2009. ‘Strong boards, CEO power and bank risk-taking’. *Journal of Banking & Finance* 33(7): 1340–1350.

Pathan, S and Faff, R. 2013. ‘Does board structure in banks really affect their performance?’ *Journal of Banking & Finance* 37(5): 1573–1589.

Phan, D H B, Narayan, P K, Rahman, R E and Hutabarat, A R. 2020. 'Do financial technology firms influence bank performance?' *Pacific Basin Finance Journal* 62: 101210.

Pierri, N and Timmer, Y. 2020. 'Tech in fin before FinTech: blessing or curse for financial stability?' IMF Working Paper 20/14.

PwC. 2016. 'Traditional financial services firms fear almost a quarter of their business is at risk from FinTechs'. News release, PwC Vietnam, 15 March.

Scott, S V, van Reenen, J and Zachariadis, M. 2017. 'The long-term effect of digital innovation on bank performance: an empirical study of SWIFT adoption in financial services'. *Research Policy* 46(5): 984–1004.

Shaban, M and James, G A. 2018. 'The effects of ownership change on bank performance and risk exposure: evidence from Indonesia'. *Journal of Banking & Finance* 88: 483–497.

Shen, Y and Guo, P. 2015. 'Internet finance, technology spillover and total factor productivity of commercial banks'. *Finance Research* 3: 160–175.

Standard Bank Group Ltd. 2016. *Annual integrated report 2016*.

Sun, J and Liu, G. 2014. 'Audit committees' oversight of bank risk-taking'. *Journal of Banking & Finance* 40: 376–387.

Talavera, O, Yin, S and Zhang, M. 2018. 'Age diversity, directors' personal values, and bank performance'. *International Review of Financial Analysis* 55: 60–79.

Teima, G, Istuk, I, Maldonado, L, Soriano, M and Wilson, J. 2022. 'Fintech and SME finance: expanding responsible access'. Fintech and the future of finance flagship technical note. Washington, DC: World Bank.

Tobias, A. 2021. ‘BigTech in financial services’. Speech to the European Parliament FinTech Working Group, IMF, Washington, DC, 16 June.

Trujillo-Ponce, A. 2013. ‘What determines the profitability of banks? Evidence from Spain’. *Accounting and Finance* 53(2): 561–586.

Vives, X. 2019. ‘Digital disruption in banking’. *Annual Review of Financial Economics* 11: 243–272.

Wang, R, Liu, J and Luo, R H. 2021. ‘Fintech development and bank risk taking in China’. *The European Journal of Finance* 27(4–5): 397–418.

Wintoki, M B, Linck, J S and Netter, J M. 2012. ‘Endogeneity and the dynamics of internal corporate governance’. *Journal of Financial Economics* 105(3): 581–606.

World Economic Forum. 2016. ‘World Economic Forum on Africa: connecting Africa’s resources through digital transformation’.
https://www3.weforum.org/docs/WEF_AF16_Report_.pdf