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Abstract

Cognizant of the recent revolution in financial technology (FinTech), this paper explores the effect of FinTech development on bank risk-taking behavior in Kenya over the period 2008 to 2021. The study first develops a FinTech index using text mining technology and then relates this index to bank-risk taking in a dynamic panel regression model. The study uncovers the following empirical results: (i) The impact of FinTech on bank's risk-taking shows a "U" shape, first falling bank risk and then rising. That is, at early stage of development, FinTech reduces risk-taking, but as key technologies mature and FinTech companies directly compete with traditional commercial banks, FinTech exacerbates risk-taking. (ii) The impact of FinTech is heterogeneous across bank sizes. Specifically, large banks appear to be more sensitive to changes in FinTech development compared to small and medium-sized banks.

1.0 Introduction

The rapid developments in financial innovation was already recognized as a stylized fact at the turn of the 21st century (Frame & White, 2004). It is worth noting that, this rapid growth in financial innovation has been enabled by advances in information and communication technologies (ICT). Broadly, the finance literature presents two opposing views on the influence of financial innovation on economic growth. The first view traditionally referred to as the "innovation-growth" hypothesis presents the bright side of financial innovation.

According to this view, financial innovation supports economic growth and poverty reduction strategies by strengthening financial development, inclusion, and efficiency (Berger, 2003). The second view christened, the "innovation-fragility" hypothesis posits that financial innovation improve the financial sector's capacity to bear risk, thereby encouraging excessive risk-taking that may lead to a financial crisis (Brunnermeier, 2009).

Financial technology (FinTech), which is broadly defined as a combination of finance and technology has become the main form of financial innovation in recent years. The Financial Stability Board (FSB) and the Basel Committee on Banking Supervision (BCBS) defines FinTech as "technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions, and the provision of financial services. Fintech spans several areas of finance including credit provision, deposits mobilization, capital raising, payments systems among others.

How does the rapid development of FinTech impact the traditional financial intermediation? This question has received increased attention in the last about 5 years. More specifically, there has been recent interest to understand whether FinTech revolution has altered the risk-taking behavior of commercial banks. Liua et al. (2017) present two channels through which FinTech development can influence bank risk-taking behavior. The first one, often christened as the *'management cost channel'* posit that Fintech innovation improves operational efficiency, reduces management cost, increases profits, and so weakens the incentives for a representative bank to take excessive risk. The second channel through which FinTech development influences bank risk-taking is the *'cost of capital channel'.* In this channel, the FinTech sector is considered as a competitor to the traditional commercial bank to the extent that it provides intermediation services. The competition for deposits raises the deposit rate, while the competition for borrowers lowers the lending rate. Ultimately, this narrows the interest margins and hence the profits of a bank. In a bid to maintain their profits, banks may resort to taking in risky projects.

Although, there is a growing number of empirical studies on the effect of FinTech innovation on bank risk preferences, empirical studies are almost exclusively based on the Chinese banking industry (see for example, Liua et al., 2017, Lee & Huang, 2019, Cheng & Qu, 2020, Wang et al., 2021, Deng et al., 2021, Wang et al., 2022). This is, however, not surprising given the tremendous progress of the FinTech sector in China. Interestingly, the literature from China provides mixed results. That is, whereas some studies indicate that FinTech development reduces bank risk-taking, other studies show that FinTech progress exacerbates bank risk-taking. Arguably, the controversial conclusions are characteristic of a new and dynamic phenomenon such as FinTech. This study contributes to the existing literature by providing fresh empirical evidence from a context that has not been investigated. Kenya is considered as the regional hub of FinTech innovation and a torchbearer in mobile money. Thus, it provides a fertile ground for investigating the effects of FinTech development. Particularly, this study, constructs (for the first time in the Kenyan context) a FinTech development index (using text mining technology) to answer the following key research questions:

- Does rapid development of the FinTech sector reduce or increase risk-taking of commercial banks in Kenya?
- Is the impact of FinTech on risk-taking heterogeneous across different bank sizes?

The answers to these questions have practical value to financial regulation. They provide insights on how commercial banks and FinTech sector can be integrated to ensure that the financial system is deepened without sacrificing financial stability.

2.0 Literature Review

FinTech, though a hot topic in recent years, is not indeed a new phenomenon. Leong and Sung (2018) observes that the seeds of the FinTech revolution were sown by the laying of the Trans-Atlantic communication cable during the 19th century. According to these authors, the FinTech revolution can be split into at least three phases. The first phase, dubbed, FinTech 1.0 provided the enabling technologies. For instance, the communication technologies as well as the introduction of computers eventually supported FinTech technologies such as SWIFT and ATMs. The second phase was the introduction of internet and the internet of things (IOT) towards the end of 1990s and early 2000s. This phase is now commonly referred to us the FinTech 2.0. The third phase, which is largely the current phase, also known as FinTech 3.0 features prominently data technologies.

There is no doubt the FinTech revolution has had significant impact on several economic outcomes. However, to track its progress and benchmark its successes over time we need an index. By its nature, the FinTech technologies are quite broad and dynamic, making the construction of an index a tricky enterprise. Further, paucity of data on the many aspects of FinTech technologies aggravate the situation. Despite these challenges, recent studies especially from China (the current powerhouse of FinTech) employ two approaches to construct a FinTech development index. The first approach involves tracking the trends of several FinTech start-ups indicators such as; number registered, capital raised, and number of financing events per given time as proxies of FinTech development (see for example, Lee & Huang, 2019). The second and novel approach uses media's attention paid to FinTech-related information to gauge the progress of FinTech. More specifically, this approach uses "Text Analytics" tools to measure the frequency of FinTech-related keywords in media outlets within a given time. Wang et al. (2021) opines that, increased media attention given to FinTech is a signal of a rapidly growing phenomenon. An increasing number of studies now employ this approach to capture the development of FinTech innovations.

A number of earlier studies on the role of Fintech on bank risk-taking often employed some measure of internet finance as an indicator of FinTech development (see for example, Pin & Yue, 2016; Guo & Shen, 2016; Qiao et al., 2018). However, Deng et al. (2021) observes that the internet finance is no longer the dominant force driving FinTech development in recent times. The authors observe that the internet finance dominated the industry in the years 1990-2010. However, from 2010 to the present FinTech is largely driven by data technologies such as big data, cloud computing, block chain, artificial intelligence etc. This realization has sparked a plethora of recent studies which use text mining approaches to construct FinTech development indices that consider the emerging data-driven technologies.

The research on the role of FinTech development on bank risk-taking behavior is still at its nascent stage and there appears no consensus yet. On one hand, there is a strand of emerging literature that indicates that advances in FinTech exacerbates bank risk-taking in general (see, Wang et al., 2021; Wang et al., 2022). Wang et al. (2022) for instance, finds that competition between FinTech startups and traditional banks increase bank risk-taking, particularly, for small and medium-sized banks in China. Further, Tseng and Guo (2018) develop a model that shows that advances in FinTech spurs credit competition between FinTech firms and traditional banks which in turn intensifies risk-taking by commercial banks. However, these authors do not verify this hypothesis with empirical evidence.

On the other hand, there is an increasing number of studies which show that Fintech development is associated with reduced bank risk-taking (see, Cheng & Qu, 2020; Deng et al., 2021 among others). This strand of the literature suggest that Fintech development reduces overall operation costs, increases bank profits, and hence weakens the motivation for banks to take excessive risks.

Overall, literature on this rapidly developing issue of Fintech seems mixed and is heavily skewed toward China. Although China is currently the hotbed of FinTech, this phenomenon seems to flourish in other countries such as in Kenya. At the moment to the best of my knowledge, little has been done to understand the effect of FinTech development on traditional intermediation in Kenya. Ntwiga (2020) examines the impact of FinTech on bank efficiency and concludes that FinTech development boosts bank operating efficiency. The current study, however, focuses on the influence of FinTech development on bank risk preferences.

3.0 Theoretical Model

The effect of FinTech on bank risk preferences is conceptualized in this study by adding a 'FinTech constraint' to a standard bank model presented by Kishan and Opiela (2000). The model is built on the following assumptions.

Assumption 1: Bank Balance Sheet

A representative profit maximizing bank accepts deposits (D) and raises equity (K) which is then split as required reserves (R) and loans to customers (L). The required reserves are assumed to yield no interest and can be expressed as a fraction of deposits (i.e., $R=\rho D$). We also define a capital adequacy ratio as $k=K/L$) and loan-deposit ratio as $D/L=(1\text{-}k)/(1\text{-}\rho)$. The simplified bank balance sheet can thus be presented as follows:

$$R+L=D+K$$

Assumption 2: Loan Market.

The bank loan market in Kenya can be deemed to be largely free except during the period September 2016 and November 2019 when lending rates were controlled. Accordingly, the loan market can be characterized by the following function: $L=L(r_L)$ where r_L refers to the lending rate and function satisfies the condition, $\partial L/(\partial r_L)<0$. That is, higher interest rates reduce lending activity.

Assumption 3: Deposit Market.

Like the loan market, deposit market in Kenya is not controlled except during the interest rate control regime (2016-2019) when there existed a deposit rate floor. Accordingly, the study assumes that the deposit interest rate (r_D) is approximately equal to the market rate (r_M) which is nearly equal to the risk-free rate (r_f). That is, $r_D=r_M=r_f$.

Assumption 4: Capital Market.

The total capital cost is viewed as consisting of two components: the real cost of deposit (i.e., $r_D/(1-\rho)$) and the risk premium (r_p) demanded by bank shareholders. Consequently, the capital return (r_K) can be written as:

$$r_K=r_P+r_D/(1-\rho)=r_P+r_f/(1-\rho).$$

Assumption 5: Interest Margin Profit

From assumption 1, we know that $k=K/L$ which implies that $K=kL$. Again, based on assumption 1, we have $R+L=D+K$ which can be rewritten as $L=K+(D-R)$. This implies that loans originate from a combination of two sources: a proportion k originates from capital, while $1-k$ originates from deposits (net of required reserves). The marginal profit of a loan is obtained as the difference between the marginal benefit of a loan (r_L) and the marginal cost of a loan- which in this case will be the $1-k$ proportion of net deposits $(r_D/(1-\rho))$. Thus, the marginal profit is given as:

$$\eta = r_L-(1-k)/(1-\rho)\ r_D = r_L-(1-k)/(1-\rho)\ r_f.$$

The study assumes $\eta>0$ due to rationality.

Assumption 6: Management Cost

The total costs of raising loans and deposits are specified as follows: $C=C_L L+C_D D$, where C_L and C_D are units costs of loans and deposits respectively and they have all the properties of a well-behaved cost function.

Assumption 7: Fintech Constraint.

The study hypothesizes that the development of Fintech affects the situation of a bank. For example, to attract potential savers and lenders a typical bank may have to alter its lending rate (r_L) as well as deposit rates (r_D). Denoting FinTech development as FT, the relationship is hypothesized as follows:

$$r_L=r_L\ (FT) \text{ with } (\partial r_L)/\partial FT<0 \text{ and } r_D=r_D\ (FT) \text{ with } (\partial r_D)/\partial FT>0.$$

Together, these conditions imply that FinTech development increases competition in financial intermediation thereby squeezing the interest rate margins (η).

Further, FinTech development can alter the risk premium component of capital return required by bank owners. Specifically, the following hypothesis is put forth: $r_p=r_p\ (FT)$ with $(\partial r_p)/\partial FT>0$. Cheng and Qu (2020) argue that risk premium increases due to the indeterminacy associated with FinTech development.

Finally, FinTech development is often accompanied by new and innovative scientific methods of production which helps a bank reduce its management cost. Thus, the following claim is advanced: $\partial C/\partial FT<0$ and $(\partial C_L)/\partial FT<0$ and $(\partial C_D)/\partial FT<0$. This management cost view presents the benefits a bank obtains by associating with the FinTech sector (Cooperation hypothesis).

The profit maximizing problem of the representative bank can be cast as follows:

$$\text{Max } \Pi = r_L L - r_D D - r_K K - C \quad \ldots\ldots\ldots\ldots\ldots(1)$$

Given the seven assumptions above, Equation (1) can be expressed as follows:

$$\text{Max } \Pi = [(r_L(FT) - (1-k)/(1-\rho) r_D(FT)) - (r_P + r_f/(1-\rho))k - (C_L(FT) + (1-k)/(1-\rho)\, C_D(FT))]L(r_L(FT)) \quad \ldots\ldots\ldots\ldots\ldots(2)$$

Solving the profit maximization problem (2) yields three important testable implications.

Testable Implication 1: Competition View.

The proliferation of FinTech enterprise spurs competition in both the loan and deposit markets. This competition squeezes interest rate margins for a typical bank. The reduced interest rate spreads imply low interest income and hence low bank profits. Due to shrinking profits, banks might be motivated to engage in risk-taking behavior to maintain their profits.

Testable Implication 2: Cooperation View.

The second important result from the model is that FinTech mitigates bank risk-taking through management cost path. According to this channel, FinTech enhances operational efficiency thereby lowering management costs which eventually increases the bank's bottom line. The elevated bank profits weaken the bank's risk appetite.

Testable Implication 3: Heterogeneity Effects.

The model solution seems to imply that the impact of FinTech on risk-taking behavior depends on the bank size. More precisely, the model suggests that the impact of FinTech on risk preferences reduces with bank size. That is, large banks have a low 'risk-taking-elasticity' to FinTech development compared to small banks.

4.0 Data, Variables, and Empirical Model

4.1 Data

For this study, the sample consist of 42 commercial banks from 2008 to 2021. The sample period begins in 2008 because the Fintech revolution began with the introduction of MPESA, a mobile phone payment network system which was launched in 2007. The introduction of MPESA paved way for the proliferation of FinTech initiatives. The other data for banking sector and macroeconomic indicators was sourced from the Central Bank of Kenya (CBK) and the Kenya National Bureau of Statistics (KNBS).

4.2 Bank Risk-taking

To characterize bank risk-taking, the study selects Z-score as the baseline indicator not only because it is widely used, but because it captures a wide array of bank risks. This time-varying proxy is computed as follows:

$$Zscore_{it}=(ROA_{it}+ETA_{it})/SDROA_{it} \quad \text{..............................} \quad (3)$$

Where for bank ***i*** at time ***t***: ROA stands for return on assets, ETA represents equity to assets ratio, SDROA represents the standard deviation of ROA (constructed as the 3-year rolling standard deviation of ROA). Z-score measures the distance from default for a typical bank. Accordingly, higher values of Z-score indicate more stability and low bank risk. In later sections, the study employs alternative measures of bank risk to check the robustness of the baseline specification.

4.3 FinTech Development Index (FT)

This study uses text mining technology to build a Fintech development index for the Kenyan economy. Text mining is a recent analytical tool that aims to extract and analyze a set of large unstructured and heterogeneous texts using some form of data mining techniques. Some commonly adopted text mining approaches include word frequency statistics, text clustering, text classification etc. This study proposes to use word frequency statistics approach. The text mining technology suggested in this study will follow four key steps: text segmentation, text extraction, text dimension reduction, and text evaluation.

The first step of text segmentation involves identifying the keywords related to FinTech. Since FinTech is a combination of finance and technology, I build a set of keywords capturing financial functions as delineated by Merton (1995). The functions include information transfer, risk management, resource allocation, clearing and payment. Regarding technology, I follow recent literature that identifies emerging technologies that closely support the financial functions. These technologies include cloud computing, big data, block chain, artificial intelligence, and biometrics. **Table 1** summarizes the keywords that are eventually used to construct the index.

Secondly, I calculate the original keywords' frequency with the help of google trends[1]. Particularly, I obtain the google trend monthly index for each of the keyword in **Table 1** over the period 2008-2021. The premise underlying this approach is that, the frequency of news items is closely related to certain socioeconomic phenomena (Askitas & Zimmermann, 2009). In this context, the amount of Fintech news is positively correlated with FinTech development. Thus, the more frequent the keywords in **Table 1** occur, the better FinTech development is inferred.

In the third and fourth steps, I use factor analysis to reduce the dimension of the data. From the previous two steps I obtained the frequency index for 17 keywords for the period 2008-2021. First and foremost, I conduct some pretests to check if the keywords are indeed factorable. The results in Table 2 show that the KMO value is 0.825 while the Barlett test p-value rejects the null hypothesis of no intercorrelations of the keywords. Together, these two metrics imply that the 17 keywords are amenable

Table 1: Initial Lexicons For The Fintech Development Index

Information transmission	Risk management	Resource allocation	Clearing and payment	Technical base
E-banking, internet banking, online banking, mobile banking.	Insurtech, internet of things, online insurance.	Peer to peer, crowdfunding, online lending.	Mobile payment, online payment, electronic pay-ment.	Big data, cloud computing, arti-ficial intelligence, block chain, biometrics.

1. Google trend collects, normalizes and scales the number of searches for all kinds of keywords provides there is a sufficient amount of searches for this keyword (Askitas & Zimmermann, 2009)

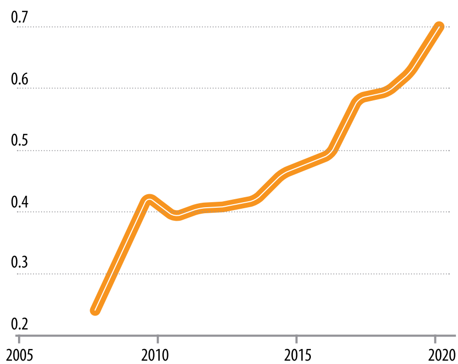
to factor analysis. Second, to determine the number of factors to retain, I follow extant literature which suggests that I retain factors with eigenvalues greater than 1. Accordingly, four factors are retained. The four factors cumulatively explain 62% of the total variation of all the 17 keywords. This indicates that the extracted factors considerably reflect the underlying information contained in the keywords. Finally, I construct a FinTech index as a weighted average of the four extracted factors (the variance contributions are used as weights). To ensure that the index is positive, I first normalize the extracted factors using the range conversion method. Therefore, the FinTech index ranges between 0 and 1, with higher values indicating more developed FinTech environment. Eventually the monthly index is collapsed into a yearly series.

Table 2: Factor analysis results

KMO	Barlett Test	Eigen Values	Cumulative variance contribution
0.825	χ^2 (136)=1390.8	λ_1=5.72	34%
	(0.000)	λ_2=1.90	45%
		λ_3=1.81	55%
		λ_4=1.11	62%

Overall, financial technology in Kenya has progressed rapidly over the period 2008-2021 (**Figure 1**). Notably, there was a sharp uptake of FinTech between 2008-2009. This early upshot can plausibly be associated with the introduction of mobile money technology (now popularly known as MPESA). However, there appears to have been a decline in FinTech activity during the period 2010-2014. The reduced FinTech activity could be due to the regulations that were rolled out during this period (such as the credit information sharing and the anti-money laundering act). The period 2015-2021 has again witnessed accelerated FinTech development particularly during the Covid-19 era.

Figure 1: FinTech development in Kenya (2008-2021)



4.4 Control Variables

Based on prior literature, this study selects control variables from three aspects: micro, industrial, and macro economy. At the micro level, four factors are chosen. First, bank size (**Size**) is computed as the natural logarithm of bank total assets. The effect of **Size** on bank risk preferences can be positive or negative. Literature is not unanimous on the direction of the effect. Interestingly, there exist hypothesis justifying each side. For example, the "too-big-to-fail" hypothesis posits that large banks can engage in excessive risk fully aware that they cannot be left to fail as that will be consequential to the economy (the moral hazard view). On the other hand, large firms have capacity to engage in asset diversification which then reduces their risk levels.

The second micro-level variable that impacts bank-risk attitude is **Liquidity**. Prior literature indicates that access to abundant liquidity aggravates bank-risk taking (Acharya & Naqvi, 2012; Hartlage, 2012; Hong et al., 2014). **Liquidity** is defined as the ratio of liquid assets to total assets. The third micro control factor is **Capital. Capital** is defined as the ratio of core capital to total assets of an individual bank. Jeitschko and Jeung (2005) provide a model that shows that capitalization can have a positive or negative effect on bank risk-taking. Thus, apriori, I expect either a positive or negative effect of capital on risk preferences of a typical bank. The fourth micro-level variable is **Efficiency** computed as the ratio of non-interest operating costs to total income. Theoretical literature suggests that efficient banks have a low appetite to take excessive risks.

At the industry level, the study controls for the effect of market structure on bank risk-preferences. Theory suggests that increased competition, hurts profits, and in a bid to maintain profitability, a representative bank may be incentivized to take more risky projects. To capture competitive forces, the study employs the Herfindahl-Hirschman Index (**HHI**), which is computed as the sum of squares of individual bank's market (for deposits) shares. Finally, to control for the effect of the business cycles on bank risk preferences, the study includes three macroeconomic variables: **GDP**, **inflation**, and growth in money (**M2**).

4.5 Baseline Model

The study applies the following model to examine the effect of FinTech on bank risk-taking:

$$\mathrm{Risk}_{it}=\mu+\rho \mathrm{RISK}_{it-1}+\gamma_1 \mathrm{FinTech}_t +\gamma_2 \mathrm{Controls}_{it}+\eta_i+\varepsilon_{it} \ \ldots\ldots\ldots\ldots\ (4)$$

Where Risk_{it} refers to the risk-taking behavior of a bank as measured by **Z-score**, $\mathrm{FinTech}_t$ refers to the economy-wide FinTech development index during a particular year- this is the main explanatory variable in this study. $\mathrm{Controls}_{it}$ represents bank specific as well as macroeconomic variables that potentially influence bank risk, η_i and ε_{it} represent respectively, the fixed effects, and the white noise disturbance term.

The lagged dependent variable in model (4) captures the dynamics of risk-analysis. Lee et al. (2021) argues that Decision-Making Unit (DMU) behavior tends to be persistent. That is, the current behavior of a DMU is often influenced by past behavior. Thus, an empirical model should take this dynamic behavior into account. However, the lagged dependent variable acting as an explanatory variable causes endogeneity problem especially in the context of panel data analysis.

In the presence of endogeneity, using OLS to estimate equation 4 will yield inconsistent and inefficient parameters. To deal with this endogeneity issue, the study employs the generalized method of moments (GMM) approach in the style of Arellano and Bond (1991) and Blundell and Bond (1998). In this approach, an endogeneous regressor is instrumented by its lagged values either in levels or in first difference. Importantly, Blundell and Bond (1998) observes that lagged levels may be weak instruments for first differenced endogeneous variables. Thus, following Blundell and Bond (1998)'s advice, I will estimate (8) using a two-step GMM with lagged differenced instruments for first-differenced variables and level instruments for level endogeneous regressors. I test the validity and strength of the instruments using the Hansen J-statistic. The J-statistic tests the null hypothesis that the instruments are exogeneous. Failure to reject this null points to valid instruments.

5.0 Empirical Results and Discussion

5.1 Descriptive Statistics

Table 3 provides the descriptive statistics for the benchmark regression model. The Z-score (the key dependent variable) is distributed with a mean of 3.306 and a standard deviation of 0.780. The values range from a minimum of 1.177 to a maximum of 5.339. With regard to FinTech, the index value ranges between 0.329 and 0.696 with a mean value of 0.485. This implies that the sampled banks are fairly heterogeneous and that Fintech development also appears heterogeneously distributed across the sampled period.

The pairwise correlation of the key variables is provided in appendix A. The correlation between the Z-score and FinTech is positive although it is not statistically significant. Though statistically weak, there appears to be a potential positive association between bank stability and FinTech development. Most of the other pairwise correlations are fairly low to cause serious multicollinearity challenges in subsequent regressions.

Table 3: Summary statistics of key variables

	N	Mean	Std. Dev.	Min	Max
Z-score	381	3.306	0.780	1.177	5.339
FinTech	381	0.485	0.101	0.329	0.696
Size	381	17.506	1.311	14.931	20.319
Liquidity	381	0.359	0.157	0.025	1.105
Capital	381	0.134	0.050	0.006	0.278
Efficiency	381	0.454	0.201	0.115	1.402
HHI	381	0.059	0.005	0.049	0.066
RGDP	381	4.661	1.907	-0.250	8.058
INFL	381	7.034	2.549	3.961	14.022
M2 Growth	381	14.245	6.143	3.890	26.521

Table 3 reports the summary statisctics of the key variables. *Z-score* proxies for bank risk-taking. ***FinTech*** is a proxy for FinTech development. ***Size*** is the ntural log of total assets, ***Liquidity*** is the ratio of quick assets to total assets. ***Capital*** is defined as the ratio of core capital to assets. ***Efficiency*** is the cost-to-income ratio. ***HHI*** is the market structure measure defined as the sum of the squares of individual deposits share. RGDP is the measure of annual economic output growth

5.2 Baseline Regression results.

This section provides the empirical results on the dynamic relationship between FinTech development and bank risk-taking. Table 4 reports the results of the two-step dynamic system GMM regression. Acoording to Table 4, the coeffient on the lagged dependent variable is positive and statistically significant at 1% providing evidence that indeed bank risk behavior shows some inertia. This supports the use of a dynamic model. The Arrellano AR(2) test as well as the sargan test of instrument validity indicate that overall, the model is appropriate for further interpretation.

More importantly, Table 4 shows that the coefficient on FinTech is statistically positive at 1% level, implying that the bank ***Z-score*** increases as financial technology develops. This result affirms ***proposition 2*** which argues that financial technology lowers the risk appetite of banks, plausibly through the management cost channel. Hu et al. (2022) finds similar result for the Chinese banking industry. These authors further indicate that, plausibly, the advances in financial technology improves the operating efficiency of banks, iincreases their profitability and so takes away the appetite to take on excessive risks.

Table 4: The effect of FinTech on Bank risk-taking

Dependent variable: Z-score	
Z-score (-1)	0.383***
	(0.060)
FinTech	2.111***
	(0.583)
Size	-0.083
	(0.110)
Liquidity	-0.509*
	(0.267)
Capital	2.944***
	(0.929)

Dependent variable: Z-score	
Cost-to-income	-1.502***
	(0.263)
HHI	-27.472***
	(8.277)
RGDP	-0.007
	(0.013)
INFL	0.008
	(0.010)
M2 Growth	-0.012*
	(0.006)
Observations	275
AR (2)	0.31
Diff-in-Hansen test (p-value)	0.892

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Two-step GMM

In the past, there has been a debate on whether FinTech and traditional commercial banks are friends or foes. The results in Table 4 support a synergistic or rather supplementary relationship between FinTech and commercial banks. There appears to be positive spillovers from advances in financial technology to the banking industry.

Focusing on the bank specific control variables, Table 4 reveals that ***Liquidity*** has a significant negative relationship with ***Z-score***, which is consistent with the theoretical proposition that abundant liquidity aggravates risk-taking (Acharya & Naqvi, 2012). ***Capital*** bears a significantly positive sign supporting the Basel accords' emphasis on the role of capital in bank stability. Further, a higher cost-income ratio bears a negative relationship with Z-score, implying that operationally inefficient banks compenstate their inefficiency by taking excessive risks in a bid to maintain their profitability. Empirical results of Table 4 also show that the market structure variable, HHI, bears a negative relationship with Z-score. This result is consistent with the "competition-fragility hypothesis". On macroeconomic controls, the results in Table 4 indicate that rapid money growth increases bank-risk taking.

5.3 Extended Regressions

Alternative Measures of Bank Risk-taking.

To check whether the baseline regression results are robust, I replace the baseline bank risk-taking measure with three other measures widely adopted in prior studies. The first measure is the asset to capital ratio, constructed by dividing total assets to core capital. Higher values of this ratio proxy excssive risk-taking. The second measure is the loan loss reserve ratio obtained as a ratio of loan loss reserves to gross loans. Similarly, elevated values of this ratio indicate higher credit risks absorbed by a typical bank. The last measure of risk employed to check robustness is the standard deviation of bank profitability. This last measure captures the bank profitability risk. The dynamic panel regression results with these alternative risk indicators are reported in **Table 5**. From the Table, it is observed that FinTech coefficients on all the three alternative measures are negative. This confirms the results obtained in the baseline regression. That is, that FinTech development has reduced risk-taking of commercial banks in Kenya.

Table 5: The effect of FinTech on Bank risk-taking: Alternative Measures of Risk

	(1)	(2)	(3)
	Asset capital ratio	Loan loss reserves	SDROA
Asset capital ratio (-1)	0.402***		
	(0.057)		
Loan loss reserves (-1)		0.150**	
		(0.075)	
SDROA (-1)			0.315***
			(0.085)
FinTech	-3.339***	-0.019	-0.013**
	(0.621)	(0.019)	(0.005)
Size	0.776***	0.008*	-0.000
	(0.139)	(0.004)	(0.002)
Liquidity	0.186	-0.000	0.004**
	(0.347)	(0.004)	(0.001)
Capital	-2.401***	0.007	0.004

	(1)	(2)	(3)
	Asset capital ratio	Loan loss reserves	SDROA
	(2.114)	(0.022)	(0.006)
Cost-income ratio	-0.206	0.083***	0.022***
	(0.317)	(0.007)	(0.005)
HHI	4.030***	0.090	0.091
	(12.496)	(0.122)	(0.060)
RGDP	0.004	-0.000*	0.000
	(0.010)	(0.000)	(0.000)
INFL	0.025**	-0.000	-0.000
	(0.012)	(0.000)	(0.000)
M2 Growth	0.015**	-0.000	0.000
	(0.007)	(0.000)	(0.000)
Observations	275	262	263
AR (2) (pvalue)	0.395	0.703	0.439
Hansen test (pvalue)	0.355	0.469	0.593

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Two-step GMM

Non-Linear Effects of FinTech Development

In the earlier stage of FinTech development, banks may benefit from reduced operational costs and improved service quality, and hence reduced incentives to take excessive risk so as to maintain profits. However, as the FinTech sector develops and ventures into more intermediation services that are traditionally a preserve of commercial banks, the latter sector loses customers to this competition and may increase risk-taking to maintain their revenue. To test this claim, a squared term of FinTech is included in the baseline regression to capture this non-linear effect. The resulting quadratic regression model is presented as follows.

$$Risk_{it} = \mu + \rho RISK_{it-1} + \gamma_1 FinTech_t + \gamma_2\ FinTech_t^2 + \sum_j \theta_j\, Controls_{jit} + \eta_{ic} + \varepsilon_{it} \quad (5)$$

Table 6: The effect of FinTech on bank risk-taking: non-linear effects

	(1)	(2)	(3)	(4)
Variables	Z-score	Asset-capital	Loan loss	SDROA
FinTech	17.510***	0.315	-0.042	-0.111**
	(6.421)	(5.329)	(0.124)	(0.048)
$FinTech^2$	-13.285**	-3.060	0.017	0.085**
	(5.556)	(4.490)	(0.097)	(0.042)
Controls	Yes	Yes	Yes	Yes
Observations	275	275	262	263
AR (2)	0.435	0.529	0.645	0.545
Hansen test (p-value)	0.395	0.316	0.273	0.173

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 Two-step GMM

Focusing on column (1) of **Table 6**, it is shown that the non-linear relation is confirmed. In particular, when a quadratic term, $FinTech^2$ is introduced into the regression, the coefficient FinTech remains positive, while the $FinTech^2$ takes on a negative and statistically significant coefficient.

Bank-size Effetcs

To test whether the effect of FinTech development on bank risk-taking varies across bank size, I create a dummy variable 'Large' taking a value of 1 if a bank has assets that exceed the median value of the commercial banking industry's distribution of total assets and 0 otherwise. Accordingly, the baseline model is extended by including an interaction term for FinTech index and the bank size as follows:

$$Risk_{it} = \mu + \rho RISK_{it-1} + \gamma_1 FinTech_t + \gamma_2 FinTech_t {*} Large + \gamma_3 FinTech_t^2 + \gamma_4 FinTech_t^2 {*} Large + \sum_j \theta_j Controls_{jit} + \eta_i + \varepsilon_{it}$$

Table 7 shows that the interaction terms, ***FinTech*Large*** and ***FinTech²*Large,*** pass the significance test for majority of the alternative risk measures. For example, in column (2), where asset to capital ratio is used as the risk-taking measure, the coefficient of ***FinTech*Large*** is negative and statistically significant at 1 percent level. Implying that, FinTech development, in its earlier stage, reduces bank risk-taking prominently for large-sized banks compared to their small counterparts. On the other hand, the coefficient on ***FinTech²*Large*** turns out positive and significant, implying that in later stages, FinTech development incentivizes banks to take on excessive risk.

Table 7: The effect of FinTech on Bank risk-taking: Size effect

	(1)	(2)	(3)	(4)
Variables	**Z-score**	**Asset-capital**	**Loan loss**	**SDROA**
FinTech	15.892**	2.977	-0.208**	-0.077**
	(6.520)	(5.792)	(0.093)	(0.037)
FinTech*Large	1.545*	-2.138***	-0.022*	-0.005
	(0.892)	(0.813)	(0.012)	(0.004)
FinTech²	-11.334**	-6.186	0.136	0.051
	(5.586)	(4.986)	(0.083)	(0.034)
FinTech²*Large	-2.299*	3.089**	0.024	0.009
	(1.189)	(1.339)	(0.016)	(0.007)
Controls	Yes	Yes	Yes	Yes
Observations	275	275	274	275
AR (2)	0.335	0.329	0.945	0.644
Hansen test	0.195	0.116	0.373	0.189

Standard errors in parentheses   *** p<0.01, ** p<0.05, * p<0.1   Two-step GMM

6.0 Conclusions

In recent years, the financial technology sector has grown in leaps and bounds triggering major changes in the financial industry. This phenomenon has attracted the attention of academic researchers mostly in China (which is arguably a FinTech torchbearer). This paper extends this research by examining the effect of FinTech development on bank risk-taking behavior of Kenyan commercial banks during the period 2008 to 2021.

The paper constructed a FinTech development index using text mining technology and factor analysis and then employed a dynamic panel model to explore the relationship between the FinTech development index and bank risk preferences.

The main empirical findings are as follows. First, the FinTech sector in Kenya show an increasing trend over the period 2008-2021. Particularly, a sharp growth is demonstrated during the Covid-19 period. Second, FinTech devlopment reveal a U-shaped relationship with bank-risk-taking. That is, in the early stages, FinTech development increased operational efficiency thereby weakening the incentive for banks to take excessive risks so as to remain profitable. However, with further advances in financial technology, FinTech companies are now direct competitors of traditional commercial banks and this has prompted banks to venture into risky projects in a bid to maintain their profits. Third, the heterogenity proposition is confirmed as large banks appear to be more sensitivity to FinTech devlopment compared to small and medium banks.

The above conclusions indicate that as FinTech and related emerging technologies mature and as technology get entrenched into financial industry there is a gradual blurring of the financial boundary. The FinTech revolution seems to carry along opportunities as well as challenges to commercial banks in Kenya. Consequently, this study recommends that, first, commercial banks should promote the use of FinTech to improve their services, lower costs and increase financial inclusion. Second, the policy authorities need to accelerate the development of a robust regulatory system that will strengthen risk management but also encourage a symbiotic development of FinTech and traditional commercial banks.

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Appendix A

Pairwise correlations

Variables	Z-score	FinTech	Size	Liquid-ity	Capital	Efficiency	HHI	RGDP	INFL	M2 Growth
Z-score	1.00									
FinTech	0.05	1.00								
Size	0.13*	0.27*	1.00							
Liquidity	-0.01	0.13	-0.04	1.00						
Capital	0.20*	-0.05	-0.13	0.30*	1.00					
Efficiency	-0.46*	0.07	-0.12	-0.19*	-0.15*	1.00				
HHI	0.08	0.39*	0.08	0.01	-0.02	0.10	1.00			
RGDP	-0.04	-0.01	-0.04	-0.01	-0.03	-0.06	-0.04	1.00		
INFL	-0.04	-0.49*	-0.12	0.00	0.01	-0.07	-0.08	-0.11	1.00	
M2 Growth	-0.05	-0.47*	-0.17*	0.03	-0.07	-0.06	-0.55*	0.22*	0.21*	1.00

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

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