Emerging Markets Review 55 (2023) 100963

Contents lists available at ScienceDirect

Emerging Markets Review

journal homepage: www.elsevier.com/locate/emr

# Bank risk-taking and competition in developing banking markets: Does efficiency level matter? Evidence from Africa

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ARTICLE INFO

*JEL classification:*
G21
L11

*Keywords:*
Risk-taking
Franchise value
Competition
Efficiency

ABSTRACT

We contribute to the existing literature on the nonlinear nexus between competition and risk-taking by exploring how differences in efficiency levels affect the risk-taking of banks when competition increases. Based on a sample of 430 African banks, this paper reveals that, banks with high and low efficiency tend to take more risk than those with average efficiency level. This study further suggests that bank specific characteristics and macroeconomic dynamics, play an important role in the competition-risk-taking nexus within African banking industry. Besides, while the penetration of African Cross-border banks does not stimulate risk-taking in the hosts domestic markets, an improvement of banking regulation (Basel 2.5, 3 and further) is mandatory to mitigate their possible adverse effects on the competition-financial stability nexus.

## 1. Introduction

Despite the extent large body of literature on the relationship between competition and risk-taking (Anginer et al., 2014; Arping, 2019; Jiménez et al., 2013; Tabak et al., 2012), no study has examined how less efficient banks would differ from more efficient ones toward risk-taking when competition increases. This study addresses the question in a nonlinear framework by examining whether the optimal values of competition above which banks modify their risk-raking are determined by their level of efficiency. To this end, we distinguish between less, averaged and highly efficient banks.

The existing literature mainly focuses on how increased competition might harm or enhance financial stability through excessive (competition-fragility) or moderated (risk-taking by banks competition -stability) (Beck et al., 2013; Berger et al., 2009; Goetz, 2018; Phan et al., 2019).

Under the first view (competition-more risk-taking), increased competition is detrimental to the bank's franchise value because it reduces the market power and loan interest rates (Demsetz et al., 1996; Marcus, 1984). In reaction to the deterioration of their franchise value induced by competitive pressures, banks may increase their exposure to risk by investing in gambling assets, which in return rises adverse selection problems (Broecker, 1990; Hellmann et al., 2000; Jiménez et al., 2013; Nakamura, 1993).

The second view (competition-less risk-taking) suggests that competition reduces banks' propensity to engage in risky activities. Considering a market where banks compete à la Cournot (i.e banks compete on the amount of loan to lend independently to their

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[1] The Authors thank anonymous reviewers, the Editor and some celleagues who helped improve the quality of this paper

https://doi.org/10.1016/j.ememar.2022.100963
Received 22 June 2020; Received in revised form 3 August 2022; Accepted 6 September 2022
Available online 13 September 2022
1566-0141/

rivals), Boyd and De Nicolo (2005) developed a model where individual loans are perfectly correlated. They hypothesised that because borrowers' default probability is reflected in the charged interest rate, a bank operating under a more competitive market would take less risk since the equilibrium loan and deposit interest rates are lower than for those in monopoly. They showed that less competitive markets are generally characterized by high loan interest rates, which, in turn, would incite borrowers to invest in risky assets with the aim of affording the loan's repayment. This mechanism is referred to as "risk-shifting."

A recent study by Martinez-Miera and Repullo (2010) explores the coexistence of the two above-mentioned views through a nonlinear relationship between competition and risk-taking. Unlike Boyd and De Nicolo (2005), Martinez-Miera and Repullo (2010) allowed for imperfect correlations among different firms' loan portfolios. By testing a range of market structures, their model showed that on top of the "risk-shifting" effect, there is a "margin" effect. The risk-shifting effect supports a negative relationship between the bank's probability of default and competition since in competitive markets borrowers are charged lower interest rates. The margin effect suggests a negative relationship between intense competition and the probability of default because within very competitive markets, banks make less revenues to comply with the capital buffers for loan losses. In the same spirit, empirical studies support the U-shape nexus between competition and risk-taking, using standard structural and non-structural measures of competition (Jiménez et al., 2013; Tabak et al., 2012).

In this paper, we investigate the relationship between risk-taking and competition relying on the African banking industry. The African banking industry fits the scope of this study since it includes banks from different economic landscape (domestic, foreign banks from developed, emerging and developing countries) which would better explain efficiency heterogeneity (Berger et al., 2000). Moreover, over the last two decades, an unprecedented growth in the expansion of so-called Pan-African banks across several African countries has been documented (Beck, 2015). Pan-African banks refer to banking groups, mainly headquartered in Africa and predominantly owned by African investors (Léon, 2016; Pelletier, 2018). In 2009, the number of African cross-border banks (CBBs hereafter) had reached 227, representing the highest proportion of foreign banks in most African countries (Beck, 2015). This spectacular trend has affected several features in this banking market, including competition (Léon, 2016), which in return would incentivise banks to take less or excessive risks.

Based on a sample including 430 African commercial banks during 2000–2015, our results confirm a nonlinear nexus between risk-taking and competition. Most importantly, our findings show that banks with high and low efficiency take more risk than those with average efficiency. Hence, the inflexion points in competition differ across efficiency levels. We also document that cost efficiency moderates the risk-taking of banks when competition increases. Besides, the expansion of Pan-African banks does not stimulate risk-taking in the domestic markets and therefore enhances financial stability. Bank characteristics and macroeconomic dynamics display significant effects on the bank risking-taking. Different robustness checks confirm the stability of our results.

This study contributes to the existing literature on the nexus between bank risk-taking and competition in several ways. First, this study is the first to examine the role of efficiency level in the nonlinear relationship between risk-taking and competition. Most existing studies document the relationship between risk-taking and efficiency (Assaf et al., 2019; Fiordelisi et al., 2011; Hughes and Mester, 1998) in a linear framework. They found either positive (good management hypothesis) or negative (cost skimping or bad management hypothesis) between the two variables (Assaf et al., 2019; Berger and DeYoung, 1997). Our procedure helps assess how the efficiency level affects the optimal values of competition in its nonlinear relationship with bank risk-taking.

The second contribution of this study is its aim to assess how Pan-African banks' penetration affects the bank risk-taking in domestic markets. Recent studies have explored the effect of foreign bank penetration on bank risk-taking in host countries as well as the difference between foreign and domestic banks in terms of risk-taking, in emerging markets and developed countries, with limited attention given to the developing markets (Chen et al., 2017; Chen et al., 2019; Wu et al., 2017). Following Gormley (2010), foreign banks' effects on domestic markets vary between developed, emerging and developing markets. Developing banking markets are less competitive, inefficient, and less sophisticated in products such that foreign CBBs' penetration would lead domestic banks to react accordingly, especially in their risk-taking behaviour. This paper is to our best knowledge, the first to explore the effect of Pan-African banks on risk-taking by employing penetration in terms of assets and the number of banks. This approach allows to quantify the effect of an increase in Pan-African banking penetration on the risk-taking of domestic banks. This approach also provides new empirical evidence on which of the two, between domestic banks and African CBBs take more risks.

Third, we complement Moyo (2018)'s study which examined the nexus between banks' soundness and competition. His research differs from ours for two reasons. First, unlike his study that included only the South African banking industry, our study consists of the entire African banking industry which enables to capture cross-country heterogeneity. According to Beck et al. (2013), heterogeneity across countries is an important feature in the competition-risk-taking because the effects differ among countries. Countries with better-developed exchange markets, more effective credit information systems and stricter activity restrictions undergo more significant effects. Second, while Moyo (2018) investigated the relationship between efficiency and soundness in a monotonic framework, our study distinguishes the level of efficiency (high, average and low) in the relationship between competition and risk-taking in order to unveil the possible heterogeneous effect of efficiency level.

Fourth, following Dinger and te Kaat (2020), on top of the two mainly employed measures of risk ($Z$-score and nonperforming loans to total assets), this paper is the first to employ the loan growth as a proxy of risk-taking in the context of Africa. As an ex-ante proxy, this measure helps examine how the increase of competition affects the loan variation in developing countries. Foos et al. (2010) establish that lending growth may be induced by the relaxation of credit conditions by the banks in order to face competition. Such relaxation might include, the underestimation of collateral or the misjudgement of the credit quality of new borrowers. Therefore, the decision on the quantity of loans to grant is not only driven by the macroeconomic dynamics but also by the intention of the bank to compete with her peers. Through this mechanism, the banks increase their exposure at default because in the lending process, the screening of borrowers is not too rigorous.

Finally, we improve the nonlinear theoretical framework proposed by Martinez-Miera and Repullo (2010), by introducing a parameter of cost efficiency which enables assessing the effect of efficiency on the probability of bank failure in the nonlinear relationship between risk-taking and competition.

The remainder of this paper is structured as follows: The second section presents a brief literature review, section 3 examines the related theoretical framework as well as the empirical strategy, section 4 presents the empirical results, and section five provides the conclusion and policy implications.

## 2. Literature review

The relationship between risk-taking and competition can be split into several class of papers. The first class of papers analyses a monotonic relationship between competition and risk-taking through two viewpoints. The competition excessive risk-taking (Competition-fragility) and the competition less-risk taking (competition-stability).

The competition excessive risk-taking view is based on the franchise value paradigm which suggests that banks in a concentrated market enjoy monopoly rents and take fewer risks to maximise their franchise value through asset quality enhancement. Marcus (1984) argues that in a more competitive banking market, banks tend to take higher risks to compensate for the drop of profits due to the fall of market power and the loan rate. Moreover, intense competition may encourage information asymmetry and moral hazard resulting from a less rigorous screening process of loan applications. Indeed, as competition grows, banks might become less stringent with their collateral requirement and screening procedures. As a result, this would lead to a greater default rate among borrowers. Allen and Gale (2004) argued that banks tend to screen, less in a very competitive market because they do not possess much information about the borrowers. Along with the competition-excessive risk-taking hypothesis, some studies document that unlike competitive banking markets, concentrated markets include big banks that can achieve economies of scale and scope as well as offer better portfolio diversifications (Boyd and Prescott, 1986; Williamson, 1986). In other words, given their size and their ability to produce efficiently, big banks take less risk when competition increases (Berger et al., 2009; Fu et al., 2014).

On the contrary, the "competition-stability" view supports the idea that banks take less risk in more competitive banking markets. Because a higher loan rate increases the probability of loan default (***risk-shifting***), in a competitive environment, this probability decreases due to lower equilibrium interest rates. Following Stiglitz and Weiss (1981), the charged interest rate on loanable funds affects the risk of loans through either adverse selection or the borrowers' future actions. In either case, a higher loan interest rate will likely lead to an increase in the default probability. Along similar lines, Boyd and De Nicolo (2005) developed a model where banks compete à la Cournot, that is banks choose simultaneously and independent the quantity of loan to grant. The risk of borrowers' projects is determined by the borrower's conditional to the charged loan rate. Through the "risk-shifting", they argue that banks tend to charge a higher interest rate in more concentrated markets, which in return increases the probability of the loan to default. Consequently, borrowers in more competitive markets that offer lower interest rates are likely to be solvent because the risk embedding the interest rate is lower. In the Boyd and De Nicolo (2005) model, the relationship between bank risk-taking and competition is monotonic. In other words, when the number of banks increases, banks decrease their risk-taking incentives. Berger et al. (2009) tested the relationship between market concentration and risk measures (including loan risk, equity capital, etc.). With a dataset of 8.235 banks from 23 developed countries, they found that banks in less competitive markets (here, more concentrated markets) were less exposed to credit risk. In the same spirit, Goetz (2018) found that increased competition improves loans' quality and decreases the bank's insolvency in the USA banking industry. Instead of considering the individual measure of bank risk, Anginer et al. (2014) related competition to the systemic risk measure. The systemic risk measure is based on the co-dependence between the distance-to-default (DD henceforth) within countries and banks. The DD is obtained from the Merton (1974)'s pricing model for the corporate debt. Results related to the above-mentioned studies suggest that competition tends to encourage financial stability through less risk-taking by banks.

The second class of papers relies on Martinez-Miera and Repullo (2010) to investigate the coexistence of the competition-risk-taking (competition-fragility) and the competition less risk-taking (competition-stability) through a nonlinear framework. Martinez-Miera and Repullo (2010) developed a model based on an oligopolistic banking market and imperfect correlation among loan portfolios. They found a nonlinear relationship between competition and bank risk-taking. They distinguished the "risk-shifting" effect from the "margin" effect. Unlike the "risk-shifting" effect, the "margin effect" implies that increased competition declines the loan interest rates and hence the bank's revenues. Therefore, banks in such market structure face the problem of insufficient capital buffer for the defaulted loans and thus become less solvent compared to those from monopolistic banking markets.

Empirically, Jiménez et al. (2013) relied on Martinez-Miera and Repullo (2010)'s nonlinear relationship between competition and risk-taking behaviour in the Spanish banking market. Their results varied depending on the used measure of market concentration used. While the nonlinearity seems to hold in the deposit and loan markets when standard market concentration measures are used, the franchise value hypothesis appears to be more significant when market power is used. Moreover, Tabak et al. (2012) employed a sample containing 376 banks from 10 Latin American countries to test a nonlinear relationship between competition and risk-taking. They used the Boone indicator to measure competition and they distinguished between high, average, and low, competitive markets. A positive nonlinear relationship is established between the competition and risk-taking for low and high competition levels, while opposite results are documented for average competition. Besides, larger banks tend to become safer due to competition's increase, while high capital ratios tend to improve banking stability within the high and average competition.

Another set of papers examine the extent to which foreign banks influence risk in the domestic host banking market. For instance, Chen et al. (2017) examined whether foreign banks take more risk than domestic banks. A sample of 1300 commercial banks in 32 emerging countries, allows to document that, foreign banks take more risk than their domestic counterparts. Aside from explaining factors of riskiness, the study emphasises information disadvantages and agency problems, among others. Besides, Wu et al. (2017) found that the presence of foreign banks incentivises domestic banks to take more risk in emerging markets.

It is important to stress that the literature on the competition-risk-taking predominantly focuses on either developed or emerging markets. However, some papers have examined the relationship between competition and risk-taking (Akande et al., 2018; Moyo, 2018; Mpofu and Nikolaidou, 2018; Oduor et al., 2017) in Africa. Akande et al. (2018) used a sample of 440 banks from 337 Sub-Sahara African countries and found that competition fosters banks to take more risk, supporting the competition-fragility hypothesis. Conversely, based on 17 banks, local and international banks, Moyo (2018), found that competition was beneficial to the financial soundness.

While the topic has gained much attention, existing studies are still controversial and some dynamics have not been entirely or partly investigated. For instance, the existing literature does not explain and test which among the most, averaged, and least efficient banks take more risks in competitive markets. What's more, the recent expansion of the so-called Panafican banks has brought in new features to the African banking industry that it is critical to examine how they affect risk-taking in Africa.

## 3. Methodology

We first present the underling theoretical framework that was first introduced by Martinez-Miera and Repullo (2010) and then explain the empirical strategy we have used to analyse our data.

### 3.1. Theoretical framework

Like Martinez-Miera and Repullo (2010), we consider the coexistence of banks and firms. Firms choose their probability of default as a function of the loan interest rate of the borrowed funds. A continuum of banks is funded with fully insured deposits and capital. They invest in a portfolio of loans. Unlike Martinez-Miera and Repullo (2010), we consider the existence of intermediation costs within banks with heterogeneous levels of cost efficiency $\varphi_i$. We distinguish between intermediation costs ($\varsigma_i$, $\alpha_i$) and $\psi_i$, the fees the banks have to pay to manage the defaulted loans. The cost efficiency $\varphi_i$, is bounded between 0 and 1 by definition. The market is considered a Cournot-type oligopoly, that is banks choose simultaneously and independent the quantity of loan to grant. In every loan granted $l_i$, there is a $\omega$ of capital and $1-\omega$ of deposit. Note that a proportion $x$ defaults, and the balance $1-x$ is repaid. $1-\lambda$ of the defaulted loans is recovered and $\lambda$ is lost. Shareholders require $\xi$ in terms of cost of capital. We also consider a separable linear intermediation cost with respectively $\varsigma_i$ and $\alpha_i$ for loan and deposit management, respectively.

Therefore, the expected pay-off of the bank can be represented as follows:

$$\pi(l_i,\omega,\varphi_i) = max l_i \int_0^{x(L)} \left[(1-x)(1+r(L)) + x(1-\lambda) - \frac{1}{\varphi_i}\psi_i x - (1-\omega) - \frac{1}{\varphi_i}(\varsigma_i+\alpha_i)\,,0\right] dF(x,p(r(L))) - \omega(1+\xi) \tag{1}$$

Where $\pi(l_i,\omega,\varphi_i)$ stands for the bank's payoff, $x(L)$ the maximum defaulted loans rate, $r(L)$ the loan rate and $F(x,p(r(L)))$ the probability distribution of the default rate. Following Martinez-Miera and Repullo (2010), the bank fails or defaults when the percentage of defaulted loans portfolio $x$ exceeds the threshold $\hat{x}$, which is derived as follows:

$$q(L,\omega,\varphi_i) = P\left\{\left((1-x)(1+r(L)) + x(1-\lambda) - \frac{1}{\varphi_i}\psi x - (1-\omega) - \frac{1}{\varphi_i}(\varsigma_i+\alpha_i)\right) < 0\right\} = P(x > \hat{x}) \tag{2}$$

where $q(L,\omega,\varphi_i)$ stands for the probability of default of the bank.

From Eq. (2), it is straightforward that the threshold or bankruptcy rate can be defined as:

$$\hat{x} = \frac{r(L) + \omega - \frac{1}{\varphi_i}(\varsigma_i+\alpha_i)}{r(L) + \lambda + \frac{\psi_i}{\varphi_i}} \tag{3}$$

Following Vasicek (2002), the cumulative distribution function of the loan rate is defined by:

$$P(x \le x) = \phi\left(\frac{\sqrt{1-\rho}\,\phi^{-1}(x) - \phi^{-1}(p)}{\sqrt{\rho}}\right) \tag{4}$$

where $p$ is the default probability of borrowing firms, $\rho$ the common correlation of loans portfolio, and $\phi$ the cumulative distribution function of the normal distribution. Under symmetry for the normal distribution, the equivalent probability of default from Eq. (4) is defined as follows:

$$q(L,\omega,\varphi_i) = P(x > x) = \phi\left(\frac{\phi^{-1}(p) - \sqrt{1-\rho}\,\phi^{-1}(\hat{x})}{\sqrt{\rho}}\right) \tag{5}$$

To compute the equilibrium on the banking market where banks compete à la Cournot, we recall that from Eq. (1), we can express the payoff function by $h(L)$ in the following:

$$h(L) = \int_0^{x(L)} \left[r(L) + \omega - \frac{1}{\varphi_i}(\varsigma_i+\alpha_i) - \left(r(L)+\lambda+\frac{\psi_i}{\varphi_i}\right)x\right] dF(x,p(r(L))) \tag{6}$$

Like Martinez-Miera and Repullo (2010), we assume that $h'(L) < 0$ and $h''(L) < 0$ to assure a unique equilibrium. To evaluate the direct effect of efficiency ("efficiency effect") on the probability of bank failure, we compute the partial derivative of (5) with respect to $\varphi_i$ which is defined as

$$\frac{dq(L,\omega,\varphi_i)}{d\varphi_i} = -\frac{\sqrt{1-\rho}}{\sqrt{\rho}}\phi\left(\frac{\Phi^{-1}(p)-\sqrt{1-\rho}\,\Phi^{-1}(\widehat{x})}{\sqrt{\rho}}\right)\left[\frac{d\Phi^{-1}(\widehat{x})}{d\widehat{x}}\left(\frac{((\varsigma_i+\alpha_i+\psi_i)r(L)+(\varsigma_i+\alpha_i)\lambda-\omega\psi_i)}{\varphi_i^{\,2}\left(r(L)+\lambda+\frac{\psi_i}{\varphi_i}\right)^2}\right)\right]<0 \tag{7}$$

The sign of (7), the first derivative is negative, suggesting that ceteris paribus, a marginal increase in efficiency, decreases the probability of bank failure. This result points out the importance of cost efficiency which is a better proxy of management quality in the banking (Assaf et al., 2019).

Under the "efficient structure hypothesis" (ESH) (Demsetz, 1973), more efficient banks may defeat the less efficient ones by increasing their market power and market share. This would likely decrease the number of banks, then increase the loan rate and consequently the probability of bank failure.

$$\frac{dq}{d\varphi} = \frac{dr(L)}{dL}\frac{dL}{dn}\frac{dn}{d\varphi} = r'(L)L'(n)\frac{dn}{d\varphi} > 0 \tag{8}$$

The proposition suggests that greater efficiency increases market concentration (referring to the ESH), and hence increases the probability of bank failure because of the rise of loan interest rate. To assess the extent to which efficiency would impact the probability of bank failure, let's consider Eq. (5) which describes the probability of bank failure and compute its partial derivative with respect to the efficiency parameter. Recall that the bank fails if the default rate $x$ is greater than the bankruptcy default rate. The derivative is computed as follows (using chain rule):

$$\begin{aligned}\frac{dq(L,\omega,\varphi_i)}{d\varphi_i} &= \frac{1}{\sqrt{\rho}}\phi\left(\frac{\Phi^{-1}(p)-\sqrt{1-\rho}\,\Phi^{-1}(\widehat{x})}{\sqrt{\rho}}\right)\\ &\times\left[\frac{d\Phi^{-1}(p)}{dp}p'(r(L))r'(L)'L'(n)\frac{dn}{d\varphi_i}-\sqrt{1-\rho}\;\frac{d\Phi^{-1}(\widehat{x})}{d\widehat{x}}\left(\frac{\left(\lambda-\omega+\frac{1}{\varphi_i}(\varsigma_i+\alpha_i+\psi_i)\right)r'(L)}{\left(r(L)+\lambda+\frac{\psi_i}{\varphi_i}\right)^2}\right)L'(n)\frac{dn}{d\varphi_i}\right]\end{aligned} \tag{9}$$

Eq. (9) implies that the relationship between competition can be moderated by the bank's efficiency level. More efficient banks may have the ability to set the lending rate lower than their competitors. As a result, by the law of demand, less efficient banks will keep higher interests' rate or invest in risky assets in order to maintain their franchise value, which will increase their risk level. Conversely, most efficient banks may decrease their interest rate which would decrease their margin effect. Reducing their margin effect implies a decrease in their ability to cover the capital buffers. Incidentally, their solvency will decrease due to the poor performance in terms of profit.

In the next section, we implement an analysis that assesses the effect of cost efficiency on the bank's default probability. We use both perfect and imperfect correlated loan portfolios with different levels of efficiency.

#### 3.1.1. Numerical analysis

We consider a simple case where deposits are fully insured with no capital requirement. We borrow Martinez-Miera and Repullo (2010) by setting a linear relationship between the probability of default of borrowers and the loan rate. The probability of default of borrowers is set to 1% if the loan rate is set to 0%, and the risk-shifting parameter equals 50%. Besides, the operating cost per unit of loan is set to 0.01. The inverse loan demand function is defined as $r(L) = 1 - 0.01L$. As in the aforementioned study, we assume a recovery rate of 45% and that cost efficiency is bounded between 0 and 1.

To examine the effect of efficiency levels on the default probability, we use different correlation values. In Fig. 1, we impose an imperfect correlation in the loan portfolio. The graph confirms the extent of relevance of cost efficiency for bank's solvency. Indeed, the lower the level of efficiency the higher the default probability of the bank. This mechanism would be referred to as "efficiency-effect" because it asserts how efficiency should be considered in the banking industry to moderate the probability of bank's failure. Moreover, the graph confirms the U-shaped relationship between competition and risk-taking in the presence of imperfectly correlated loans (Martinez-Miera and Repullo, 2010).

We further examine the relationship between competition and efficiency in case of perfectly correlated loans. Results are displayed in Fig. 2 and suggest that more efficient banks are safer than their peers. These results are in line with Assaf et al. (2019), who found that during normal times high cost efficiency strengthens bank's solvency.

### 3.2. Empirical strategy

This study examines to what extent least efficient differ from most efficient banks in the competition-risk-taking behaviour. To that end, measurement of competition, efficiency, and risk are required. They are measured as follows:

*3.2.1. Measurement of efficiency*

To estimate cost efficiency, we employ the intermediary approach according to which the bank collects deposits to produce loans ($y_1$) and other earning assets ($y_2$) (Matousek et al., 2015; Shaban and James, 2018). To this end, banks use three inputs: labour, financial capital, and physical capital. The price of labour ( $w_1$) is defined by the ratio of personal expenses over total assets, the price of physical capital ( $w_2$) by the ratio of other operating expenses over the book value of fixed assets and the price of capital ( $w_3$) by the ratio of total interests over the total deposits and short-term funding. The total cost ($TC$) is hence the sum of total interests paid, personal, and other operating expenses. To consider differences in risk profiles, Berger and Mester (1997) suggest including equity, and it is quadratic terms in the Translog cost function. Like in (Shaban and James, 2018), technological changes over time are captured by the time trend and its quadratic term. Because of heterogeneity among African countries, we follow Gaganis and Pasiouras (2013) by grouping these countries into three groups: High, average, and low development level.

We use a parametric approach to estimate efficiency, knowingly the Stochastic Frontier Analysis (SFA). Unlike the non-parametric method, the SFA approach has the advantage of defining the stochastic term's distribution function that helps alleviate potential bias due to random events and measurement errors (Kumbhakar and Lovell, 2003).

Instead of the commonly used Translog, we employ the Fourier flexible function (FFF hereafter), which provides better approximates of the underlying cost function for the entire sample (Fenn et al., 2008). The FFF adds on trigonometric terms to the standard Translog function that allows for more flexibility and hence provides more efficient estimates (Assaf et al., 2019; Berger and Mester, 1997; Cyree and Spurlin, 2012). The function is formalized as follows:

$$
\begin{aligned}
ln\left(\frac{TC_{it}}{w_3}\right) = {} & \beta_0 + \sum_{l=1}^{2}\beta_l lny_{l_{it}} + \sum_{m=1}^{2}\varphi_m ln\left(\frac{w_{jit}}{w_3}\right) + \beta_2 lnE_{it} + \beta_3 T \\
& + \frac{1}{2}\left[\sum_{j=1}^{2}\sum_{m=1}^{2}\delta_{mj} ln\left(\frac{w_{jit}}{w_3}\right)\left(\frac{w_{jit}}{w_3}\right) + \sum_{j=1}^{2}\sum_{m=1}^{2}\theta_{mj} lny_{mit} lny_{jit} + \theta_1 (lnE_{it})^2 + \theta_2 T^2\right] \\
& + \sum_{j=1}^{2}\sum_{m=1}^{2}\alpha_{mj} ln\left(\frac{w_{jit}}{w_3}\right) lny_{mit} + \sum_{m=1}^{2}\gamma_{mj} ln\left(\frac{w_{jit}}{w_3}\right) lnE_{it} + \sum_{m=1}^{2}\omega_{mj} lny_{mit} lnE_{it} + \sum_{m=1}^{2}\tau_{mj} ln\left(\frac{w_{jit}}{w_3}\right) T \\
& + \sum_{m=1}^{2}\varphi_{mj} lny_{mit} T + \theta_3 T lnE_{it} + \sum_{f=1}^{2}\left[\psi_f cos(Z_f) + \eta_f sin(Z_f)\right] + \sum_{f=1}^{2}\sum_{g=1}^{2}\left[\lambda_{fg} cos(Z_f + Z_g) + \vartheta_{fg} sin(Z_f + Z_g)\right] \\
& + \delta DEVEL + lnv_i + lnu_i
\end{aligned}
\tag{10}
$$

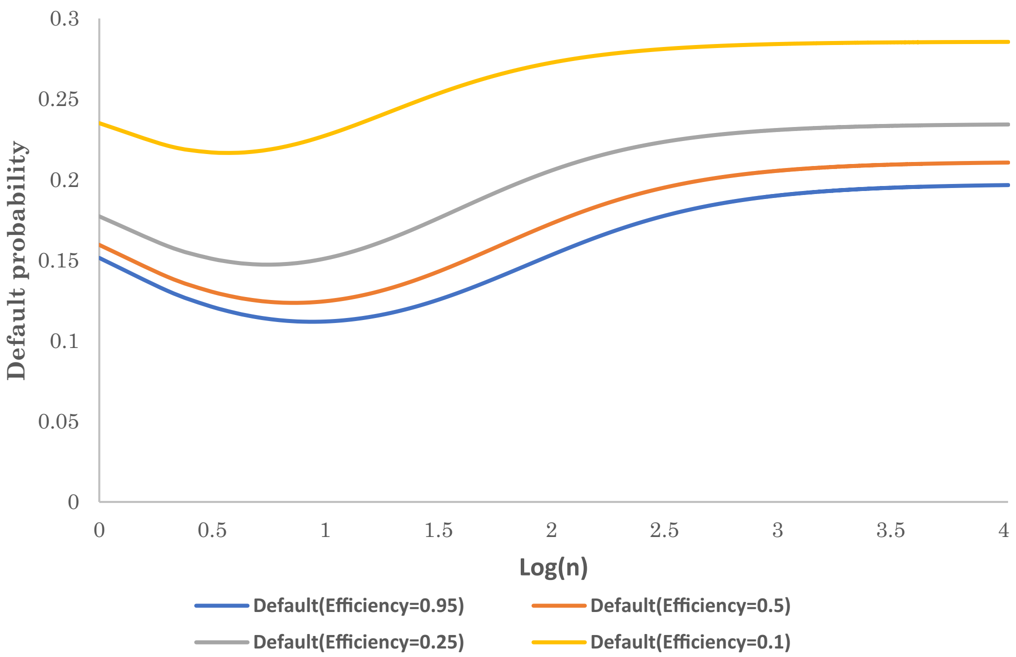


**Fig. 1.** Imperfectly correlated loans Default probability with different efficiency levels: ρ =20%.

where $TC_{it}$, $y_{kit}$ and, $w_{lit}$ stand respectively for the total cost, the output $k$ and the input $l$ prices of bank $i$ at time $t$. $v_i$ and $u_i$ represent respectively the measurement errors and the allocative efficiency. $T$ stands for the time trend, $Z_f$ are rescaled variables of outputs,[2] $E_{it}$ represents the book value of equity for bank $i$ at time $t$, $ln$ is the natural log and $DEVEL$ a dummy variable which distinguishes high, medium and low degree of development for African countries. The cost efficiency score is therefore defined by:

$$CEFF_{it} = \frac{C^{min}}{C^a} = \frac{exp[c(y^f, w^f)]^* exp\left(lnu_c^{min}\right)}{exp[c(y^f, w^f)]^* exp\left(lnu_c^f\right)} = \frac{u_c^{min}}{u_c^a} \tag{11}$$

Where $CEFF_{it}$ stands for the cost efficiency of bank i at time t, $C^{min}$ the minimum cost, $C^a$the actual cost, exp. the exponential, $u_c^{min}$the minum cost form the translog cost function as mentioned before.

### 3.2.2. Measurement of competition

Indirect and direct measure are used to measure competition. Indirect measure includes market power measured by the Lerner Index. As direct measure of competition, we adopt the use of Panzar-Ross continuous-time curve like in (Jeon et al., 2011).

a) Lerner Index

Used to assess the market power of a single firm in the industry, this measure has been widely used in the banking literature as an indirect measure of competition (Beck et al., 2013; Fu et al., 2014; Léon, 2016; Lozano-Vivas and Weill, 2012). It has the advantage of being more flexible and has less data requirements for its construction. It is defined as the ratio of price-cost margin to the price. Formally, the Lerner index is computed is defined as

$$LIF_{it} = \frac{P_{it} - MC_{it}}{P_{it}} \tag{12}$$

Where[3] $LIF_{it}$ refers to as the Lerner index derived from FFF cost function, $P_{it}$ the price and $MC_{it}$ the marginal cost, of bank $i$ at time $t$. While $MC_{it}$, the marginal cost is derived from a Translog cost function in line with (Chen et al., 2017; Lozano-Vivas and Weill, 2012). The price is the ratio of revenue to the total assets. The marginal cost is derived from Eq. (10) using a single output corresponding to the total assets. Defined as the first derivative of the cost function, the marginal cost is presented as:

$$MC_{it} = \frac{dTC_{it}}{dY_{it}} = \left[\beta_1 + \delta_{11} lnY_{it} + \sum_{m=1}^{2} \alpha_{mj} ln\left(\frac{w_{jit}}{w_3}\right) + \vartheta lnE_{it} + \theta_4 T - \mu_f\left[\psi_f sin(Z_f) - \eta_f cos(Z_f)\right]\right] \frac{TC_{it}}{Y_{it}} \tag{13}$$

b) Panzar-Ross continuous-time curve

Following Bikker and Haaf (2002)'s strategy like in (Jeon et al., 2011), we estimate time-varying PRH as a direct competition measure. It is defined through the following equation:

$$ln(R_{it}) = \alpha_i + \left[\beta_1 ln\left(W_{1i,t}\right) + \beta_2 ln\left(W_{2i,t}\right) + \beta_3 ln\left(W_{3i,t}\right)\right] exp(\varepsilon^* T) + \sum \delta_i X_{it} + e_{i,t} \tag{14}$$

Where $i$ and $t$ stand for the bank and the time, $R_{it}$ is the financial income as the measure of the bank's revenue, $W_{li,\,t}$ stand for the same as in Eq. (10), $X_{it}$ represents a number of covariates including bank size[4] dummies, capital ratio, net loan to total assets and the ratio of total operating income to interest income. Following Bikker and Haaf (2002) and Jeon et al. (2011), the time trend $T$ helps evaluate whether competition has varied over time as a result of structural exogenous changes including the expansion of African cross-border banking, technological changes and different regulations. This approach is important since ignoring these market dynamics would lead to biased and imprecise estimation of the PRH (Bikker and Haaf, 2002). $\varepsilon$ is a parameter that assesses the time-variation of competition within a banking industry. The generally used PRH is obtained by summing up the three elasticities of the input prices i.e., $\beta_1 + \beta_2 + \beta_3$ estimated using nonlinear least squares. The time-continuous Panzar-Rosse is an extension of the approach that is defined as ( $\beta_1 + \beta_2 + \beta_3$) $exp$ ($\varepsilon$ * $T$). A statistically significant $\varepsilon$ in the model indicates time-variation of competition within the banking industry. PHR statistics is set such that $PRH < 0$ corresponds to a monopolistic market, $PRH_{it} = 1$ refers to perfect

[2] The rescaling process follows that of Fenn et al. (2008). $Z_f$ is defined as follows: $Z_f = 0.2x\pi - \mu_f x Y_{mini} + \mu_f x Y_i$, where $Y_i$ stands for the output value in the sample for bank i. $\mu_f$ is defined by: $\mu_f = \frac{[(0.9x2\pi)-(0.1x2\pi)]}{Y_{maxi}-Y_{mini}}\pi$ refers to a number approximately equal to 3.141593.

[3] In some recent studies, the concept of adjusted Lerner index have been proposed by (Restrepo-Tobón and Kumbhakar, 2014) to circumvent the weakness of conventional Lerner index. In this study, we maintain the traditional Lerner index which is mainly used in the literature and for which the results are not very different from modified version.

[4] The dummy variables are classified as follows:

$$Dummyp25 = 1 \ if \ Assets_{it} < q_1\left(AAssets_{jt}\right)$$

$$Dummyp50 = 1 \ if \ Assets_{it} \geq q_1\left(AAssets_{jt}\right)\left\langle q_2\left(AAssets_{jt}\right)\right.$$

$Dummyp75 = 1$ $if$ $Assets_{it} > q_2(AAssets_{jt}) \leq q_3(AAssets_{jt})$ with $q_h$the qth quartile of Assets in Country j

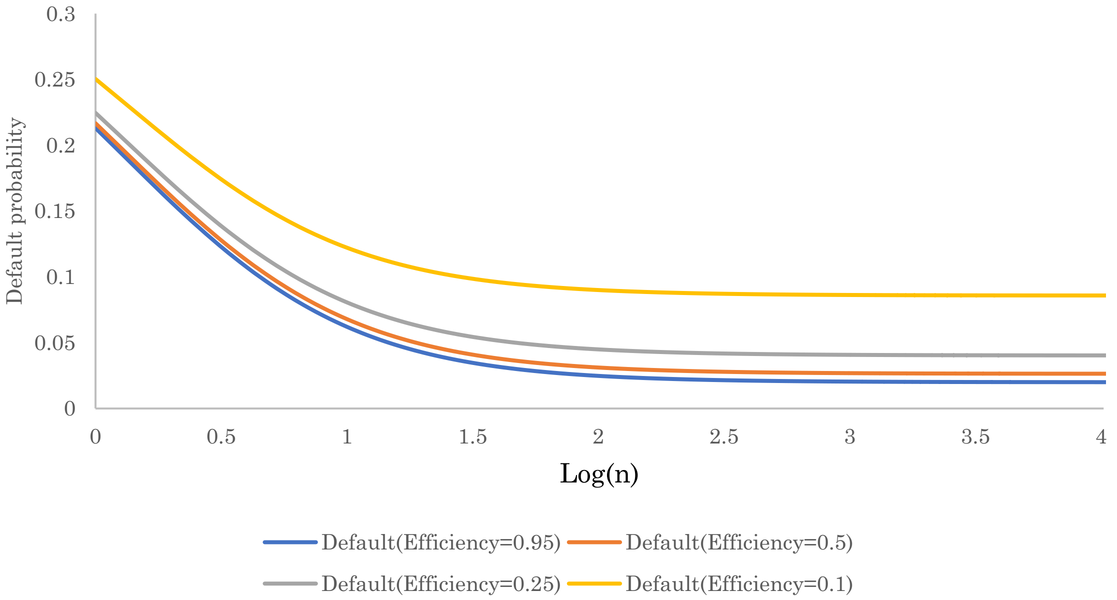


**Fig. 2.** Default probability vs competition across different levels of efficiency: perfectly correlated loans.

competition and $0 < PRH < 1$ for monopolistic competition.

### 3.2.3. *Measurement of risk*

In this study, we employ two commonly used measures of risk-taking, the *Z*-score, and the non-performing loan to total assets. The Z-score is generally used as a proxy of risk, when the sample includes non-listed banks. The literature suggests that a bank fails when the operating losses are less than the amount of equity (Lepetit and Strobel, 2015; Mare et al., 2017). Assuming that the profit of the bank is normally distributed and using symmetry, the probability of bank failure is defined as

$$p(-\pi > E) = p(\pi \leq -E) = p(ROA \leq -EA) = p\left(\frac{ROA - \mu_{ROA}}{\sigma_{ROA}} \leq \frac{-EA - \mu_{ROA}}{\sigma_{ROA}}\right) = p\left(Z \leq \frac{-(EA + \mu_{ROA})}{\sigma_{ROA}}\right) = 1 - p\left(Z \leq \frac{(EA + \mu_{ROA})}{\sigma_{ROA}}\right) \tag{15}$$

Eq. (15) implies that the probability of failure increases with the value of Z-score $Z = \frac{EA + \mu_{ROA}}{\sigma_{ROA}}$ i.e. the higher the *Z*, the lower the probability of default. Following recent literature (Ashraf, 2017; Boubakri et al., 2020; Dbouk et al., 2020; Wu et al., 2020; Wu et al., 2017; Wu et al., 2019), we use a three-year rolling window to compute $\sigma_{ROA}$. Beck et al. (2013) and Schaeck and Čihák (2010) argue that it is preferable to use short time rolling windows to compute $\sigma_{ROA}$ because with long periods, the Z-score variation may be driven by the change in capital and profit within the bank. It also helps keep the panel structure of the dataset and alleviate the bias induced by gaps in the panel (Beck et al., 2013). After computing the Z-score, we control for skewness by using its natural log ($\ln(Z)$). In line with Zhu and Yang (2016) and Anginer et al. (2014), we use non-performing loan provision which is defined as a ratio of bad loans to the total assets. This proxy evaluates the extent to which increased competition may affect the quality of loan. In the robustness checks, following Dinger and te Kaat (2020), we employ the loan growth ($LGR_{it}$) as a proxy of risk-taking. As an ex-ante proxy, this measure helps examine how the increase in competition affects risk-taking in terms of lending growth. Foos et al. (2010) establish that lending growth may be induced by the relaxation of credit conditions by the banks in order to face competition. Such relaxation might include, the underestimation of collateral or the misjudgement of the credit quality of new borrowers. In that perspective, the decision on the quantity of loans to grant is not only driven by the macroeconomic dynamics but also the intention of the bank to compete with her peers in the market. A high variation in loans implies a high risk-taking since the amount related to the exposure at default of the bank increases. To compute the proxy of loan growth, we rely on Foos et al. (2010) and Ho et al. (2021) who defined the loan growth as:

$$LGR_{it} = \frac{Total\ loan_{it} - Total\ loan_{it-1}}{Total\ loan_{it-1}} \tag{16}$$

Because African countries display differences in terms of macroeconomic dynamics and banking market structures, we use the abnormal loan growth rate ($ALGR_{it}$) to account for the embedding heterogeneity (Foos et al., 2010). The Abnormal loan growth rate refers to the difference between the loan growth of a specific bank and the median of the country's aggregated loan growth. It is defined as;

$$ALGR_{it} = LGR_{it} - LGR_{jt}{}^{median} \tag{17}$$

Where $LGR_{jt}^{median}$ stands for the median of loan growth rate in country *j* at time *t* and $ALGR_{it}$ the abnormal loan growth of bank *i* at time *t*.

### 3.2.4. Control variables

Among bank-specific variables, we use size, liquidity, and diversification. Size (log of total assets) is used to capture big banks' ability to cope with risk-taking (Agoraki et al., 2011; Cubillas and González, 2014; Jiménez et al., 2013; Tabak et al., 2012; Wu et al., 2017). The literature suggests a negative relationship between risk and bank size. Large banks have more advantage in risk diversification. Through their ability to cherry-pick customers and to access information, they are able to mitigate the risk induced by the competition. The liquidity (measured as the ratio of liquid assets over the total assets) helps banks mitigate external shocks (Wu et al., 2017). Very liquid banks may take more risk because excess liquidity help banks cope with risk effects. Income diversification is computed as the ratio of non-interest income over the total operating income (Demirgüç-Kunt and Huizinga, 2010; Wu et al., 2017). This is variable is likely to have a negative effect on risk-taking. However, banks with high degree of diversification may take more risk since they can compensate potential losses through diversification.

Macroeconomic variables include GDP growth, inflation and financial development indicator. GDP growth and inflation have been used in the literature to explore how business cycle and economic activity may affect the risk-taking in the banking industry (Agoraki et al., 2011; Chen et al., 2017; Cubillas and González, 2014; Louhichi et al., 2020). While good economic performance may moderate financial frictions and incentivise banks to take more risk, hight inflation rate may increase the borrowing costs and lead the rise of bank risk exposition. However, economic growth may reduce the bank risk because during expansion, lending is not highly exposed to default. The financial development indicator, the credit to private over the GDP is also considered. High degree of financial development may imply a lower degree of information asymmetry and therefore low risk exposition for banks. However, in case the high degree of financial development is induced by intense competition, financial development may increase bank risk-taking.

Institutional quality includes governance variables and legal origin. Governance variables, which are namely regulation, governance, corruption, political stability exhibit high correlations. To circumvent any multicolinearity related problem, we follow (Chang et al., 2019; Godspower-Akpomiemie and Ojah, 2021; Seven and Coskun, 2016) and employ principal component analysis. This approach helps extract one or more component (s) that broadly explains the total variation of the governance variables. This new variable captures the extent to which governance affect the risk-taking in the banking. We argue that good governance reduces information asymmetry and the delinquency of borrowers which reduces the bank risk-taking.

### 3.2.5. Baseline regression

We test the relationship between competition and bank risk-taking relying on Salas and Saurina (2002) and Jiménez et al. (2013). They used a dynamic panel approach because risk is a persistent variable. For instance, nonperforming at time $t-1$ affects the amount at time *t* because the overwriting overlap. To that end, our baseline regression is presented as follows:

$$RISK_{it} = \alpha_0 + \gamma_{it} RISK_{it-1} + \alpha_1 COMP_k + \alpha_2 COMP_k^{\ 2} + \alpha_3 CEFF_{it} + \sum_{i=1}^{k} \beta_i X_{it} + \sum_{i=j}^{q} \delta_j F_{jt} + \mu_i + \varepsilon_{it} \tag{18}$$

Where $RISK_{it}$ and $RISK_{it-1}$denotes the risk of bank *i* at time *t* and its one-year lagged variable, $COMP_{kt}$ represents the competition in country *k* at time *t*, $CEFF_{it}$ the cost efficiency of bank *i* at time *t*, $X_{it}$, $F_{jt}$, $\mu_i$, $\varepsilon_{it}$ represents respectively, the bank-specific variables, macroeconomic factors, unobserved bank's individual effects, and the error the term. In addition, $\boldsymbol{\alpha_i}$, $\boldsymbol{\beta_i}$ and $\boldsymbol{\delta_j}$ stand for different covariates sensitivities to the bank risk-taking and $\gamma_{it}$ the persistence parameter of risk measure.

To assess the effect of efficiency level, we include dummies of efficiency which is high if cost efficiency is higher than the 3rd quartile, low if the value is lower than the 1rst quartile and medium (Average) otherwise. Therefore, we test for the following specification:

$$\begin{aligned} RISK_{it} &= \alpha_0 + \gamma_{it} RISK_{it-1} + \alpha_1 COMP_k + \alpha_2 COMP_k^{\ 2} + \alpha_3 Efficiency\ level_{it} + \alpha_4 COMP_k{}^{*}Efficiency\ level_{it} \\ &\quad + \alpha_5 COMP_k^{\ 2}{}^{*}Efficiency\ level_{it} + \sum_{i=1}^{k} \beta_i X_{it} + \sum_{i=j}^{q} \delta_j F_{jt} + \mu_i + \varepsilon_{it} \end{aligned} \tag{19}$$

Where all the variables stand for the same as in Eq. (18) and *Efficiency level*$_{it}$ for the efficiency level bank *i* at time *t*.

As our baseline regression is dynamic, parameters are estimated using system Generalized Method of Moments (GMM here after) as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). GMM is preferred over OLS because OLS would produce biased and inconsistent estimators due to the correlation of the lagged dependent variable with the fixed effect in the error term (Roodman, 2009). Roodman (2009) suggests that using GMM solves many econometric issues, omitted variables, unobserved heterogeneity, and reverse causality. Although we have included bank characteristics, macroeconomic and institutional variables, this study may be subjected to unobserved heterogeneity or variables omission that might affect bank risk-taking. For instance, more skilled managers may take less risk than their peers because of their ability to screen and cherry-pick the least risky customers. Moreover, reverse causality may affect the relationship between competition and risk-taking. In the same spirit, Beck et al. (2013) suggests that countries with adequate credit information are more stable than others. It is possible that a bank's propensity to take more risk in countries with less information sharing is higher than their counterparts within high and effective information sharing landscape. Moreover, a financial system with strong regulatory control is subjected to a high number of restrictions that may alter banks to take more risk. To confirm the validity of our instruments, Hansen J test is used and to test first-order Arellano and Bond (1991) correlation is employed.

**Table 1**
Descriptive statistics and Mean comparison *t* test.

| Variable | Obs | Mean | Std. Dev. | Min | Max | T test between CBB and Domestic banks |
|---|---|---|---|---|---|---|
| Bank specific variables | | | | | | |
| *ln_ZC* | 2820 | 3.096 | 0.366 | 0.000 | 8.184 | 0.0071 |
| *SROA* | 2828 | 1.288 | 2.151 | 0.000 | 30.095 | 0.0750* |
| *NPLTA* | 2663 | 3.571 | 5.777 | 0.000 | 81.273 | −1.8937*** |
| *LIQUID* | 2506 | 0.271 | 0.166 | 0.000 | 0.905 | 0.0132** |
| *ETA* | 3935 | 0.144 | 0.123 | 0.000 | 0.997 | −0.0285*** |
| *LIQUID* | 3892 | 33.53 | 19.767 | 0.068 | 99.4116 | 3.1125** |
| log_*SIZE* | 3935 | 5.560 | 1.833 | −10.982 | 11.132 | −0.2385*** |
| *CEF* | 3220 | 0.795 | 0.132 | 0.146 | 0.970 | −0.0163*** |
| *DIV* | 3655 | 33.707 | 18.704 | 0.000 | 100.000 | 2.1428*** |
| Market Structure measures | | | | | | |
| *PRH* | 1963 | 0.496 | 0.224 | 0.147 | 0.9030 | |
| Macroeconomic and institutional | | | | | | |
| *GOV* | 3776 | 1.13e-10 | 1.000 | −1.4865 | 2.9139 | |
| *INFL* | 3886 | 8.598 | 27.712 | −35.836 | 1096.678 | |
| *DPRIVATE* | 3464 | 24.89428 | 25.70361 | 0.198286 | 160.125 | |
| *GDPgrowth* | 3902 | 5.4402 | 27.3445 | −62.0759 | 1230.363 | |

Windmeijer (2005) finite-sample correction to standard errors is used to correct for potential related bias.

### 3.3. Data

This study employs bank-specific, macroeconomic, and governance variables. Bank-specific variables are retrieved from Bankscope Bureau van Dijk in Brussels,[5] a commonly used database for banks' data covering around 90% of the banking systems of most countries. Values are converted in millions of US dollars for all the banks to assure measurement homogeneity. The original sample includes 530 active commercial banks during 2000 to 2015. Non-Active banks are directly filtered out from the database to avoid any survivorship bias. All observations with negative equity, operating expenses, and zero fixed assets book value are cancelled to avoid misinterpretations or bias. Some countries such as Guinea Bissau, Congo, Eritrea, and Sao Tomé are cancelled out for cost efficiency estimation. At the same time, Equatorial Guinea is dropped for Lerner index analysis because of insufficient data. Unconsolidated data are used to avoid any multiple records. To construct the ownership structure, this study combines information from Beck et al. (2014) list[6], Bankscope, and bank's websites to distinguish CBBs from domestic banks. A careful attention is paid on the description included in the Bankscope data, and are completed by the two above mentioned sources. This information enables distinguishing African CBBs from non-African CBBs. The ownership is assigned if at least 50% is controlled by a category of shareholders. The final sample consists of 429 banks from 48 countries, as presented in Appendix 2. Hence, in the final sample, 208 (48.48%) are CBBs, and 221 (51.52%) are host country banks. Accounting for cross-border origin yields 149 (71.6%) subsidiaries from Africa and 59 (28.4%) from other continents (mostly from developed and emerging markets).

Macroeconomic variables were obtained from the World Bank data library. Economic variables (inflation, growth rate) were retrieved from the Word development indicator database, while financial data (credit to private ratio) were retrieved from the Global Financial development database. Institutional variables include political stability, governance, corruption perception, and regulation. To avoid any multicollinearity issues due to the high correlation among the institutional variables, we use a single indicator constructed from a Principal component analysis approach. The component used represents 77.84% of the total variance.

## 4. Empirical results

### 4.1. Summary statistics and correlation

Summary statistics and mean comparison *t*-test are presented Table 1. The transformed Z's average value is about 2.954 with 0.402 standard deviations entailing a low dispersion in bank's solvency and risk among different banks ranging from 0 to 8.189. The nonperforming loan to total assets ratio and the standard deviation of the return on assets means are respectively 3.571% and 1.288%. Their standard deviations are large, approximately equal to 200% of the mean value, suggesting a great heterogeneity among the sample's banks in terms of loan quality. The Lerner index, a measure of market power, shows an average value of 27.1%, which means

[5] This database was closed since 31 January 2017, but same data are distributed by Fitch-Connect which I accessed from Paris Dauphine University's Library for data comparison.

[6] On page 60 of this book, it is provided the list of cross-border banks operating in Africa, their origin, ownership, host countries and where their headquarters are located.

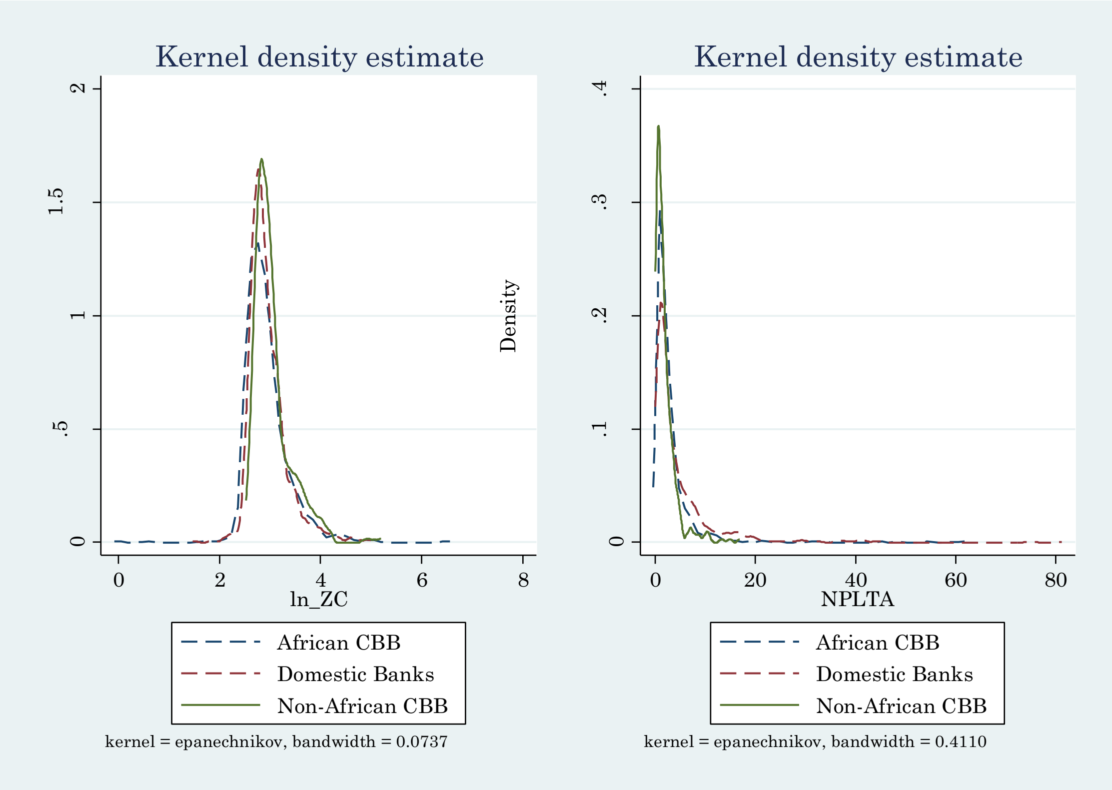


**Fig. 3.** Kernel density estimation of risk measures.

that each bank earns 27.1% on its activities on average. Its standard deviation is approximately 70% of its average value, indicating a great heterogeneity among banks in market power.

At the market structure's level, Panzar and Rosse (1987) H statistic is used to measure competition. Regarding PRH statistics, it displays an average value of 0.49 with a standard deviation representing about 45% of the mean, which indicates heterogeneous banking markets in the selected sample. These results suggest that the selected banking markets are structured as monopolistic competition as its average value falls into the interval starting from 0 to less than 1. The HHI index suggests the same results of heterogeneity among banking markets concentration. Although some markets tend to be more concentrated, the expansion of cross-border banks has increases competition and eroded the former very concentrated African banking systems. On average, African CBB represents 40% and 33% of African banking in terms of number and assets. Their distribution across the continent is heterogeneous, with some countries having a low number of ACBBs.

Bank-specific variables such as liquidity, size, diversification, capital ratio also suggest heterogeneity among African banks. The average capital ratio's is roughly equal to 14.4% which is higher than the required regulatory 8% threshold. The cost efficiency's mean is 79.5%, with the most efficient bank displaying an efficiency score of 97% while the least efficient achieves a 14.6% score. Macroeconomic variables also show heterogeneity among African banking systems either in terms of economic performance (inflation, growth rate) or governance.

Because our results include cross-border subsidiaries and domestic banks, we perform both at comparison test as well as a kernel density representation. Kernel density estimation is presented in Fig. 3. The figure shows no significant difference in terms of distribution among the three types of banks. For the Z score, an important number of values are located around the mean, except for the non-African CBB that has another pic at a point higher than the sample's mean. The same applies to the NPLTA, which is truncated between 0 and 100%, although an important number falls above the mean.

In terms of t-test, on average, domestic banks exhibit significantly higher cost efficiency, bigger size, and lower loan quality compared to cross-border Banks. In terms of the Z score, there is no significant difference between the two categories of banks. Nevertheless, NPLTAs show a statistically significant difference between domestic and CBBs. CBBs show lower values than domestic banks. It is important to note that most differences among these banks are driven by non-African CBBs, specifically when market power and efficiency are concerned because a more detailed analysis shows that the ranking in terms of market power is ascendingly African CBB, Domestic Banks, and Non-African CBBs.

The pairwise correlation is presented in Table 2. A higher number of our variables show significant correlation values, although the latter are not much higher to suspect any multicollinearity problem.

**Table 2**
Correlation matrix among main variables.

| | *ln_ZC* | *SROA* | *NPLTA* | *LI* | *PRH* | *HHI* | *LIQUID* | log_*SIZE* | *DIV* | *ETA* | *CEF* | *GOV* | *FINDV* | *GDPgrowth* | *INFL* | *LEGOR* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *ln_ZC* | 1 | | | | | | | | | | | | | | | |
| *SROA* | −0.322*** | 1 | | | | | | | | | | | | | | |
| *NPLTA* | −0.106*** | 0.136*** | 1 | | | | | | | | | | | | | |
| *LI* | 0.102*** | 0.00734 | 0.0591* | 1 | | | | | | | | | | | | |
| *PRH* | 0.0730** | −0.0021 | 0.0261 | 0.0471 | 1 | | | | | | | | | | | |
| *HHI* | 0.0531** | −0.0045 | −0.0117 | 0.137*** | 0.242*** | 1 | | | | | | | | | | |
| *LIQUID* | −0.00963 | −0.00253 | −0.101*** | 0.273*** | 0.0397 | 0.215*** | 1 | | | | | | | | | |
| log_*SIZE* | 0.204*** | −0.228*** | −0.0202 | 0.0743*** | 0.110*** | −0.167*** | −0.0603*** | 1 | | | | | | | | |
| *DIV* | −0.0787*** | 0.116*** | −0.0128 | 0.274*** | −0.0818*** | 0.0840*** | 0.249*** | −0.115*** | 1 | | | | | | | |
| *ETA* | −0.0827*** | 0.251*** | 0.136*** | 0.00252 | 0.0191 | −0.0188 | −0.0372* | −0.258*** | 0.101*** | 1 | | | | | | |
| *CEF* | 0.0613** | −0.0233 | 0.0206 | 0.0830*** | 0.143*** | −0.0601*** | −0.209*** | 0.0424* | −0.225*** | 0.0386* | 1 | | | | | |
| *GOV* | −0.00203 | 0.00607 | −0.0702*** | −0.0269 | −0.280*** | 0.0738*** | −0.00993 | −0.0457** | −0.142*** | 0.0000104 | 0.0685*** | 1 | | | | |
| *DPRIVATE* | −0.0156 | −0.0415* | 0.0678** | −0.156*** | 0.0914*** | 0.0470** | −0.110*** | 0.170*** | −0.205*** | 0.0177 | 0.102*** | 0.334*** | 1 | | | |
| *GDPgrowth* | 0.00542 | 0.0478* | −0.0293 | 0.0316 | 0.0601** | −0.0648*** | −0.0372* | 0.015 | −0.00678 | −0.0223 | 0.0510** | 0.0672*** | 0.0000955 | 1 | | |
| *INFL* | −0.0246 | 0.0962*** | −0.0275 | 0.0675*** | 0.0616** | 0.119*** | 0.0828*** | −0.0722*** | 0.0195 | 0.0194 | −0.114*** | −0.0933*** | −0.0427* | −0.0949*** | 1 | |
| *LEGOR* | 0.0289 | −0.122*** | 0.136*** | 0.0939*** | −0.258*** | −0.00000158 | 0.0760*** | 0.196*** | 0.160*** | −0.180*** | −0.182*** | −0.205*** | −0.170** | −0.166*** | −0.0443** | 1 |

This table presents pairwise correlation matrix among different variables of this study. Specifically, risk measures, bank specific, macroeconomic, and institutional control controls. ***, **, * denote statistical significance at level 0.1%, 1% and 5% respectively. Variables' definition is presented in Appendix 1.

The Z score and NPLTA show positive linear correlations with Lerner Index and PHR. There is a possibility of a nonlinear relationship between PRH statistics and risk measures. Note that size shows an interesting correlation with all risk measures.

### 4.2. Main results

#### 4.2.1. Preliminary tests and baseline results

This study aims to assess the link between competition and bank risk-taking in the African banking industry by emphasising the role of efficiency and African cross-border banking expansion. In terms of empirical implementation, our regression model includes a one-year lagged variable of the dependent variable (the risk-taking measure) which arises the problem of dynamic bias (Nickell, 1981). In fact, the lagged variable ($RISK_{it-1}$) is correlated with the error term which leads to inconsistent OLS estimates. Moreover, a possible correlation of $RISK_{it-1}$with the error term arises endogeneity problem. As a preliminary analysis, we run an OLS regression of the baseline regression and perform endogeneity test. The related results are reported in Table 3. Overall, the endogeneity test confirms the presence of endogeneity in our data and the related results are not much different from those obtained by GMM estimation. However, the literature favours the use of the system GMM over the OLS (Roodman, 2009). For instance, Jiménez et al. (2013) has used the system GMM for their study on the relationship between competition and risk-taking for the Spanish banking industry given the dynamic fashion of the risk-taking dynamics. Therefore, the remaining part of this paper can rely on the results obtained from the GMM.

**Table 3**
OLS Baseline results.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| VARIABLES | $lnZ_t$ | $lnZ_t$ | $lnZ_t$ | $lnZ_t$ |
| $lnZ_{t-1}$ | 0.45812*** | 0.34233*** | 0.48574*** | 0.25267*** |
| | (0.02520) | (0.04640) | (0.02850) | (0.06215) |
| $LIF_t$ | 0.57823*** | 0.58363** | | |
| | (0.19453) | (0.27071) | | |
| $LIF_t^2$ | −0.48314* | −0.72608* | | |
| | (0.29177) | (0.42258) | | |
| $CE_t$ | 0.09355 | 0.31511*** | 0.37203*** | 0.30770* |
| | (0.08708) | (0.11636) | (0.11764) | (0.17024) |
| *African Cross* | 0.04063** | 0.05872** | −0.00110 | 0.01730 |
| | (0.01938) | (0.02465) | (0.02355) | (0.03314) |
| $Liquid_t$ | −0.00032 | 0.00040 | −0.00056 | −0.00238** |
| | (0.00055) | (0.00074) | (0.00076) | (0.00107) |
| $\log(SIZE)_t$ | 0.02713*** | 0.03564*** | 0.04838*** | 0.10250*** |
| | (0.00733) | (0.01029) | (0.00875) | (0.01332) |
| $DIV_t$ | −0.00220*** | −0.00139 | 0.00016 | −0.00058 |
| | (0.00070) | (0.00095) | (0.00084) | (0.00122) |
| $GOV_t$ | 0.00480 | −0.00415 | −0.01597 | −0.01011 |
| | (0.01025) | (0.01356) | (0.01376) | (0.01957) |
| $INFL_t$ | −0.00038 | 0.00114 | −0.00184 | −0.00134 |
| | (0.00129) | (0.00195) | (0.00148) | (0.00252) |
| $FINDEV_t$ | −0.00015 | −0.00058 | 0.00038 | −0.00065 |
| | (0.00042) | (0.00053) | (0.00066) | (0.00091) |
| $GDPgrowht_t$ | 0.00216 | 0.00480 | −0.00174 | −0.00542 |
| | (0.00248) | (0.00353) | (0.00408) | (0.00587) |
| $GDPgrowth_{t-1}$ | 0.00060 | −0.00218 | 0.00364 | −0.00023 |
| | (0.00286) | (0.00410) | (0.00369) | (0.00563) |
| $PRH_t$ | | | −0.45202 | −1.39718*** |
| | | | (0.31244) | (0.44721) |
| $PRH_t^2$ | | | 0.34832 | 1.29180*** |
| | | | (0.29450) | (0.42003) |
| Constant | 1.34246*** | 0.87662*** | 1.07288*** | 3.25684*** |
| | (0.12515) | (0.21080) | (0.16584) | (0.50068) |
| Threshold | 0.60 | 0.40 | 0.65 | 0.54 |
| Observations | 1364 | 911 | 961 | 805 |
| R-squared | 0.27132 | 0.23410 | 0.31785 | 0.2805 |
| Endogeneity test | | | | |
| Durbin | 10.788*** | | 424.69*** | |
| Wu-Hausman | 10.618*** | | 869.905*** | |

This table presents OLS and IV estimates of the link between competition and bank-risk taking behaviour. Competition is measured by Lerner Index ($LIF_t$) and Panzar-Rosse time continues-time curve ($PRH_t$), the risk by the natural log of Z score ($lnZ_t$). Bank characteristics includes (size $\log(SIZE)_t$, liquidity($Liquid_t$), diversification index ($DIV_t$)), macroeconomic indicators include (the GDP growth ($GDPgrowht_t$), inflation ($INFL_t$) and financial development variable ($FINDEV_{it}$)), and the first component retrieved from a PCA analysis of governance ($GOV_t$) measures are included in this estimation. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

**Table 4**
Baseline regression: Competition vs Risk.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | $lnZ_t$ | $lnZ_t$ | $NPLTA_t$ | $NPLTA_t$ |
| $RISK_{t-1}$ | 0.55598*** | 0.33858*** | 0.65439*** | 0.75785*** |
| | (0.05354) | (0.02385) | (0.00253) | (0.00972) |
| $LIF_t$ | 0.72772*** | | −1.71034*** | |
| | (0.17072) | | (0.34307) | |
| $LIF_t^2$ | −0.80250** | | 4.48215*** | |
| | (0.25369) | | (0.49187) | |
| $CE_t$ | 0.15633** | 0.28055*** | −0.07943 | −0.40569*** |
| | (0.05964) | (0.07886) | (0.18589) | (0.14840) |
| *African Cross* | 0.03282* | 0.00050 | −0.51771*** | −0.00811*** |
| | (0.01911) | (0.00065) | (0.06398) | (0.00086) |
| $Liquid_t$ | −0.00044 | −0.00107* | −0.01669*** | −0.01448*** |
| | (0.00043) | (0.00056) | (0.00130) | (0.00093) |
| $\log(SIZE)_t$ | 0.04045*** | 0.07589*** | −0.10426*** | −0.08743*** |
| | (0.00792) | (0.01346) | (0.02600) | (0.01598) |
| $DIV_t$ | −0.00156** | 0.00065 | 0.00607*** | −0.00493*** |
| | (0.00053) | (0.00066) | (0.00120) | (0.00094) |
| $GOV_t$ | −0.00409 | −0.01428 | −0.08520*** | −0.06539*** |
| | (0.00863) | (0.01178) | (0.02552) | (0.01666) |
| $INFL_t$ | 0.00037 | −0.00206** | −0.00895*** | −0.00100 |
| | (0.00097) | (0.00091) | (0.00165) | (0.00089) |
| $FINDEV_{it}$ | −0.00037* | 0.00018 | 0.00980*** | −0.00218*** |
| | (0.00022) | (0.00052) | (0.00141) | (0.00061) |
| $PRH_t$ | | −0.98548** | | 2.21716*** |
| | | (0.39029) | | (0.82415) |
| $PRH_t^2$ | | 0.90740** | | −1.92249*** |
| | | (0.34644) | | (0.72538) |
| Constant | 1.33444*** | 0.00000 | 49.62370*** | 93.20101*** |
| | (0.14817) | (0.00000) | (17.06773) | (5.07085) |
| Threshold | 0.55 | 0.54 | 0.19 | 0.58 |
| Hansen *P*-value | (0.182) | (0.616) | (0.410) | (0.553) |
| AB Residual test AR (1) | −4.98*** | −4.51*** | −3.00*** | −3.41*** |
| AB Residual test AR (1) | (0.865) | (0.754) | (0.867) | (0.215) |
| Observations | 1118 | 805 | 1276 | 739 |
| Number of banks | 224 | 132 | 240 | 130 |

This table presents the GMM estimation of the link between competition and bank-risk taking behaviour. Competition is measured by Lerner Index ($LIF_t$) and Panzar-Ross time continues-time curve ($PRH_t$), while the risk is measured by the natural log of Z score ($lnZ_t$) and by Nonperforming Loan to total assets ($NPLTA_t$). Bank specifics (size $\log(SIZE)_t$, liquidity($Liquid_t$), diversification index ($DIV_t$)), macroeconomic (inflation ($INFL_t$)), financial development variable ($FINDEV_{it}$), and the first component retrieved from a PCA analysis of governance ($GOV_t$) measures are included in this estimation. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

The first results are presented respectively in Table 3, Table 4, Table 5 and Table 6. In Table 3 and Table 4, the analysis displays results related to the link between risk-taking and competition in the baseline regression from Eq. (18). Because, Z score is generally skewed, we follow Beck et al. (2013) and use the natural log of Z score.

Along with Durbin's first and second-order autocorrelation tests, Hansen J suggests that our instruments are valid, and the model is well specified. Like in Agoraki et al. (2011), the coefficients of the lagged variable of risk measure are positive and statistically significant, implying risk persistence. As in Jiménez et al. (2013), the relationship between risk measures and market power is nonlinear. The link implies that an increase in market power improves banks' solvency or decreases bad loans up to an optimal level above which a margin increase in market power will lead to a decline of solvency or an increase in bad loans.

The results in Table 4 suggest that an increase of 1 unit in market power will increase bank solvency until the market power exceeds the threshold, (which is found to be 0.55 from the GMM and 0.6 from the OLS). Above these values, a marginal increase in market power undermines the bank's solvency or increase its risk-taking incentives.

The threshold of the relationship between market power and nonperforming loans to total assets ($NPLTA_t$) is approximately 0.19 and 0.58 when competition is measured by PRH statistics. In fact, a marginal rise in market power beyond that threshold will create an incentive for banks to engage in risky activities in order to recover their franchise value. Conversely, the findings reveal an inverse U-shaped relationship between PRH and risk-taking measures. In the first stage, an increase in competition incentivises banks to take risk but above the optimal threshold, which is approximately equal to 0.54, a marginal increase in competition reduces bank risk-taking. These findings are consistent with Agoraki et al. (2011), Beck et al. (2013) and Fu et al. (2014), who focused on transition economies, worldwide emerging-developed economies, and Asia-Pacific emerging economies.

The relationship between bank cost efficiency and solvency is positive and statistically significant as predicted by the theoretical framework. The results from columns (1) and (2) of Table 4 (similar to those from OLS) suggest that one standard deviation increase in

**Table 5**
Competition and risk: Efficiency effect.

| | (1) | (2) |
|---|---|---|
| VARIABLES | $lnZ_t$ | $NPLTA_t$ |
| $RISK_{t-1}$ | 0.55598*** | 0.84600*** |
| | (0.05354) | (0.00475) |
| $PRH_t$ | 0.32657*** | 0.29758*** |
| | (0.01076) | (0.07609) |
| $PRH_t^2$ | 0.17038 | −0.21204*** |
| | (0.45126) | (0.06764) |
| $\boldsymbol{CE_t}$ * $PRH_t$ | −0.42956 | −0.35377*** |
| | (0.42689) | (0.09191) |
| $\boldsymbol{CE_t}$*$PRH_t^2$ | −1.16275* | 0.24746*** |
| | (0.64077) | (0.08081) |
| $\boldsymbol{CE_t}$ | 1.36456** | 0.09892*** |
| | (0.58744) | (0.02450) |
| Constant | 0.50088** | 0.93988*** |
| | (0.17134) | (0.17080) |
| Controls | Yes | Yes |
| Hansen P-value | (0.246) | (0.553) |
| AB Residual test AR (1) | −4.49*** | −3.41*** |
| AB Residual test AR (1) | (0.538) | (0.215) |
| Observations | 805 | 739 |
| Number of banks | 132 | 130 |

This table presents the GMM estimation of the link between competition and bank-risk taking behaviour. We moderate the effect of competition on risk measure by interacting the first and the second order term of Competition by cost efficiency score. Competition is measured by Panzar-Rosse continues-time curve ($PRH_t$), while the risk is measured by the natural log of *Z*-Score ($lnZ_t$) and by Nonperforming Loan to total assets ($NPLTA_t$). Standard errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

cost efficiency, increases the solvency by 1.02. Consistent results were documented by Assaf et al. (2019), Chen et al. (2017) and Fiordelisi et al. (2011). The findings indicate that inefficiency driven by bad management might lead to excessive risk-taking by managers. Similarly, cost efficiency is negatively associated with non-performing loan supporting the good management hypothesis.

Our results in Table 4 and Table 6 display a negative and significant correlation between liquidity and Z score, entailing that high liquidity result in less bank's solvency. The literature suggests that more liquidity may impact the bank return volatility, depending on the economy's state(Bordeleau and Graham, 2010). During recession, banks tend to hold excessive liquidity while during expansion, banks invest in order to maximise their profits. These results are consistent with Tabak et al. (2012), who found that Latin American emerging economies were booming to the extent that banks would have engaged more in business than carrying much liquidity.

Nonetheless, Chen et al. (2017) focused on emerging markets, including Latin America, Asia, and Eastern and Central Europe from 2000 to 2014, and observed an insignificant positive link. This opposite result may result from the study period that includes the subprime crisis, which was essentially a liquidity crisis period.

Besides, Zheng et al. (2019) study on the US banking industry documented a negative link between liquidity creation and risk of failure from 2003 to 2014. They reveal a more pronounced magnitude during the financial crisis implying that economic performance and business cycles can explain the direction of the linkage between risk-taking and liquidity.

Similar to previous studies, we gauge the importance of size in the explanation of bank risk-taking. Across all columns in Table 3 and Table 4, size displays positive and significant coefficients relative to *Z*-score. This result supports the idea that large banks take less risk in African banking. Almost identical results are found in previous studies (Beck et al., 2013; Chen et al., 2017; Goetz et al., 2016). Moreover, the effect of size is economically significant. Indeed, an increase of size by 1% increases the solvency of the bank 0.04% to 0.08%. In the meantime, a 1 unit increase in size, decreases the NPLTA by 9.2%. These results support Boyd and Prescott (1986)'s view, suggesting that large banks are less fragile because of their ability to achieve economies of scope and scale, higher market share and market power, and risk diversification advantages, which enabled them to earn more profits compared to small banks. In contrast, some empirical results negatively correlate size and solvency (Berger et al., 2009; Tabak et al., 2012). These studies document that rather than enjoying risk mitigation due to their scale and market power, some large banks seem to invest in risky assets to maximise their profits and franchise value. To emphasise the importance of a bank's size in the relationship between bank risk-taking and competition, Tabak et al. (2012) and Chen et al. (2017) went further by examining the interaction of size with different levels of competition (high, average, and low, respectively) and splitting size into large and small banks. They support the view that larger banks tend enhance their solvency from a competitive market whereas smaller banks tend to take more risks when new banks enter the market. Due to the low banking competition in Africa, larger banks are likely to benefit from economies of scale, and better diversification and consequently secure greater solvency.

Regarding diversification, it displays a weak negative effect on the bank's solvency implying that more diversified banks in terms of income tend to take more risk. The negative effect may be driven by the volatility of non-interest income. Although it is well

**Table 6**
Risk vs competition: the effect of efficiency level.

| | (1) | (2) | (3) |
|---|---|---|---|
| Efficiency level | High | Average | Low |
| VARIABLES | $lnZ_t$ | $lnZ_t$ | $lnZ_t$ |
| $lnZ_{t-1}$ | 0.38639*** | 0.36734*** | 0.37819*** |
| | (0.01904) | (0.01660) | (0.01817) |
| $LIF_t$ | 0.60019*** | 1.06355*** | 0.98876*** |
| | (0.09151) | (0.10151) | (0.08551) |
| $LIF_t^2$ | −0.40248** | −1.27842*** | −1.10708*** |
| | (0.13322) | (0.13231) | (0.10886) |
| *Efficiency level* | −0.08269*** | 0.02641 | 0.02272 |
| | (0.01414) | (0.02166) | (0.02412) |
| $LIF_t$ * *Efficiency level* | 0.98478*** | −0.31192** | −0.28107* |
| | (0.10006) | (0.14196) | (0.15870) |
| $LIF_t$ * *Efficiency level* | −1.75447*** | 0.71173*** | 0.30193 |
| | (0.15941) | (0.21278) | (0.22057) |
| *African Cross* | 0.04543*** | 0.03995*** | 0.03874*** |
| | (0.01131) | (0.01136) | (0.01127) |
| $Liquid_t$ | −0.00017 | −0.00026 | 0.00009 |
| | (0.00022) | (0.00023) | (0.00023) |
| $\log(SIZE)_t$ | 0.04008*** | 0.03494*** | 0.03685*** |
| | (0.00444) | (0.00486) | (0.00481) |
| $DIV_t$ | −0.00283*** | −0.00283*** | −0.00282*** |
| | (0.00027) | (0.00027) | (0.00025) |
| $GOV_t$ | 0.01269** | 0.00903 | 0.00611 |
| | (0.00542) | (0.00554) | (0.00540) |
| $INFL_t$ | −0.00083** | −0.00073* | −0.00069 |
| | (0.00040) | (0.00043) | (0.00042) |
| $FINDEV_t$ | −0.00062*** | −0.00047** | −0.00043** |
| | (0.00014) | (0.00016) | (0.00014) |
| $GDPgrowht_t$ | 0.00430*** | 0.00433*** | 0.00426*** |
| | (0.00129) | (0.00124) | (0.00121) |
| $GDPgrowth_{t-1}$ | −0.00143* | −0.00302*** | −0.00203** |
| | (0.00076) | (0.00071) | (0.00073) |
| Constant | 0.38639*** | −0.31192** | −13.40792*** |
| | (0.01904) | (0.14196) | (2.15044) |
| Optimal threshold | 0.37 | 0.66 | 0.44 |
| Hansen P-value | (0.271) | (0.234) | (0.373) |
| AB Residual test AR (1) | −4.82*** | −4.82*** | −4.73*** |
| AB Residual test AR (1) | (0.802) | (0.676) | (0.689) |
| Year dummy | Yes | Yes | Yes |
| Observations | 1118 | 1118 | 1118 |
| Number of banks | 224 | 224 | 224 |

This table reports a two-step system GMM estimation of the link between risk (here *Z*-score, $lnZ_t$) and the Lerner index ($LIF_t$) considering the level of efficiency which higher (HE) if its value is higher than the 3rd quartile, low is the value is lower (LE) than the 1rst quartile and medium (ME) otherwise. Bank specifics (size $\log(SIZE)_t$, liquidity($Liquid_t$), diversification index ($DIV_t$)), macroeconomic (GDP growth ($GDPgrowht_t$) and its one-year lagged value, inflation ($INFL_t$)), financial development variable ($FINDEV_{it}$), and the first component retrieved from a PCA analysis of governance ($GOV_t$) measures are included in this estimation. *African Cross* stands for African cross-border bank. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

established that greater diversification is a source of risk reduction, Chen et al. (2017) found similar results for Latin American emerging markets. They argue that comparative advantages may drive this effect for banks not relying only on traditional business model consisting of revenues from lending.

As to macroeconomic variables, our study shows a positive and significant impact of economic growth on bank solvency entailing that bank risk-taking depends on the economic performance and that banks tend to be less risk-exposed during economic booms. Similar results were found by Chen et al. (2017) and Jiménez et al. (2013) for emerging economies and Spain.

The possible explanation would be that banks face a high demand for loans during an economic boom from both corporate and retail, which are less likely to default. While inflation seems to exhibit a higher impact on bank risk-taking, governance, which is obtained from the principal component analysis, including the governance effectiveness, control of corruption, the rule of law land regulation, is positively and significantly related to bank's solvency. Like Uddin et al. (2020), who led a similar study on emerging countries, our results suggest that institutional quality reduces bank's propensity to take many risks.

Another important variable in the risk-taking analysis in Africa is the ownership structure. Following Beck et al. (2014) and Léon

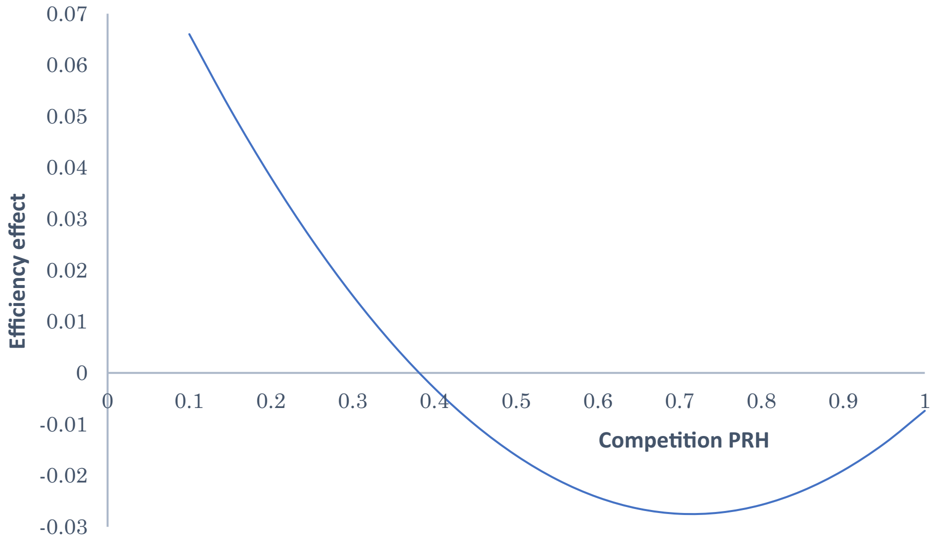


**Fig. 4.** Marginal Effect of Cost efficiency.

(2016), over the last two decades, the African banking industry has witnessed a considerable expansion of Pan-African cross-border. We examine the implications of Pan-African banks on African bank risk-taking. Results suggest a positive and significant sign with solvency, implying that African CBBs concurs a lot with the financial stability of African banking by taking less risks.

### *4.2.2. Considering efficiency level in the nexus between competition and risk*

We explore the effect of efficiency in the relationship between competition and risk-taking in the banking industry as specified in (19). We first interact cost efficiency and the measure of competition, and then assess the optimal value of market power and competition for low, average and high efficiency. A bank is classified in High efficiency category if its cost efficiency is higher than the third quartile, low efficiency if lower than the first quartile and average if efficiency ranges between the first and the third quartiles. Unlike Chen et al. (2017), who measured efficiency by overheads to total operating income, we measure efficiency using a Fourier flexible SFA which has the advantage of comparing any bank to the its best possible practice.

Table 5 shows significant effect of the interaction terms of cost efficiency, specifically in column (2) where risk is measured by nonperforming loans.

To assess the marginal effect of cost efficiency, we compute the first derivative of (2) with respect to cost efficiency, i.e. $\frac{\partial NPLTA_{it}}{\partial CE_{it}} = 0.24746 PRH_t^2 - 0.35377 PRH_t + 0.09892$ for which roots are 0.38 and approximately 1 moving from monopolistic to perfect competition with an inflexion point approximately equal to 0.71. We further present the nonlinear effect in Fig. 4. The marginal effect of cost efficiency on risk is nonlinear, and varies across different market structure from monopolistic market to perfect competition. Like Assaf et al. (2019) who suggested that cost efficiency enables banks to survive during financial crisis times, our results suggest that cost efficiency enables banks to mitigate the effect increased competition on their risk-taking.

Furthermore, in Table 6, we examine the effect of efficiency level in the relationship between competition and risk-taking.). Interaction terms with market power for first and second-order terms are statistically significant for most and averaged efficient banks while only the first second order interaction terms are statistically significant for least efficient banks. These results rank the optimal thresholds, with averagely efficient banks coming first with 0.66 followed by the least efficient banks (0.44) and most efficient banks (0.37).

These results indicate that the most efficiency banks take less risk as long as the market power is less than 0.37. Above that threshold, highly efficient banks take more risk to enhance their franchise value. Averagely efficient banks seem to be more prudent because this threshold is equal to 0.66. They probably adjust their level of efficiency and market power to maintain or increase their solvency. They likely do not engage in risky activities due to the rise in market power, but instead screen their customers rigorously.

Following Chen et al. (2017), least efficient banks may suffer from the "bad management" (Berger, 1995). According to the "bad management" hypothesis, less rigorous managers may take significant risks because they have been unable to assign real scoring to borrowers and assess the real value of pledged collateral, and have exhibited less efficiency in the monitoring of issued loans.

Since the Lerner index is an inverse measure of market competition, we borrow Tabak et al. (2012)'s strategy by using a direct measure of competition. Unlike their studies, we use a continuous-time Panzar and Rosse (1987) curve following Jeon et al. (2011). We take into account countries where results indicate a significant variation in competition. A higher PRH indicates a higher value of competition since when PRH is lower than 0, we have a monopolistic market, and when it is equal to 1, the market is under perfect competition. When it lies between 0 and 1, the market is said to be under monopolistic competition. Results on the link between risk-taking and PRH are presented in Table 7. We use the natural log of Z-score to measure risk. As in the previous findings, our results support a significant nonlinear relationship between competition and risk-taking entailing the coexistence of both competition-

**Table 7**
Competition (Panzar-Ross) vs. risk.

| | (1) | (2) | (3) |
|---|---|---|---|
| Efficiency Level | High | Average | Low |
| **Variables** | $lnZC_t$ | $lnZC_t$ | $lnZC_t$ |
| $RISK_{t-1}$ | 0.31906*** | 0.32720*** | 0.32646*** |
| | (0.03163) | (0.03350) | (0.03070) |
| $PRH_t$ | −0.67131** | −1.32611*** | −0.74576** |
| | (0.28364) | (0.35058) | (0.29149) |
| $PRH_t^2$ | 0.50252** | 1.35431*** | 0.66993** |
| | (0.25353) | (0.31727) | (0.26045) |
| $PRH_t$ * *Efficiency Level* | −1.18926*** | 0.64494** | −0.43883* |
| | (0.43246) | (0.27193) | (0.24910) |
| $PRH_t^2$**Efficiency Level* | 1.45942*** | −0.88061*** | 0.42852* |
| | (0.37711) | (0.25200) | (0.22195) |
| *Efficiency Level$_t$* | 0.22517** | −0.08792 | 0.06348 |
| | (0.11315) | (0.06436) | (0.05988) |
| *African Cross* | 0.00094*** | 0.00069** | 0.00054* |
| | (0.00032) | (0.00030) | (0.00031) |
| $LIQUID_t$ | −0.00181*** | −0.00178*** | −0.00149*** |
| | (0.00039) | (0.00039) | (0.00037) |
| log$(SIZE)_t$ | 0.07487*** | 0.06980*** | 0.06993*** |
| | (0.00668) | (0.00627) | (0.00670) |
| Constant | 19.14654*** | 18.60060*** | 19.57944*** |
| | (4.76090) | (4.31496) | (4.22695) |
| Threshold | 0.47 | 0.72 | 0.54 |
| Hansen P-value | (0.416) | (0.477) | (0.380) |
| AB Residual test AR (1) | −4.31*** | −4.27*** | −4.37*** |
| AB Residual test AR (2) | (0.547) | (0.493) | (0.671) |
| Year Dummy | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Observations | 805 | 805 | 805 |
| Number of Banks | 132 | 132 | 132 |

This table presents the System GMM estimation of the link between competition and bank-risk taking behaviour. Competition is measured by the Panzar-Ross time continues-time curve ($PRH_t$), while the risk is measured by the natural log of Z score ($lnZC_t$). We distinguish different levels of efficiency, including and each variable takes value 1. High level (High) if its value is higher than the 3rd quartile, low level if the value is lower (Low) than the 1rst quartile and average (Average) otherwise. These dummies are interacted with measures of competition. Bank specifics (size log$(SIZE)_t$, liquidity($Liquid_t$), diversification index ($DIV_t$)), macroeconomic (GDP growth ($GDPgrowht_t$) and its one-year lagged value, inflation ($INFL_t$)), financial development variable ($FINDEV_{it}$), and the first component retrieved from a PCA analysis of governance ($GOV_t$) measures are included in this estimation. *African Cross* stands for African cross-border bank. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

fragility and competition-stability.

In other words, under a given threshold, banks increase their risk-taking when competition increases to maintain their franchise value. Above that threshold, a marginal increase in market competition will stimulate banks to take less. In this the case, the latter banks probably take less risk because above that value, interest rates will significantly fall down. Considering the level of efficiency in this approach is worth being highlighted. In fact, like in the previous analyses, we split our sample into three efficiency levels: high, average, and low. In terms of main effects, results suggest that highly efficient banks tend to be resilient, while average and low-efficiency banks tend to be less solvent in more competitive markets. The thresholds are respectively 0.47, 0.72, and 0.54 for most, averagely, and least efficient banks. Results related to coefficients presented Table 7 and Fig. 5 show that as competition grows, average efficient banks tend to be more prudent in risk-taking compared to their peers. However, as the banking market tends to move to perfect competition, more efficient banks exhibit high solvency than their peers.

#### 4.2.3. Nonperforming loans and competition: The role of efficiency levels

We follow Anginer et al. (2014) among others who used non-performing loans to total assets ($NPLTA_t$) as a proxy to risk-taking in the banking industry. Non-performing loans are an indicator of the amount of loans that fail to be repaid by the borrowers at the expiration date and hence an indicator of risk in the banking industry. Pertinent results are reported in Table 8.

The results support a nonlinear relationship between market power and non-performing loans, suggesting that a marginal increase in market power decreases bank's bad loans under a given threshold. Above this threshold, an additional market power will likely lead the bank to take more risk. Besides, the effect differs across banks depending on their efficiency level. Results suggest that highly efficient banks reduce their nonperforming loans more than averagely and least efficient banks when their market power rises higher.

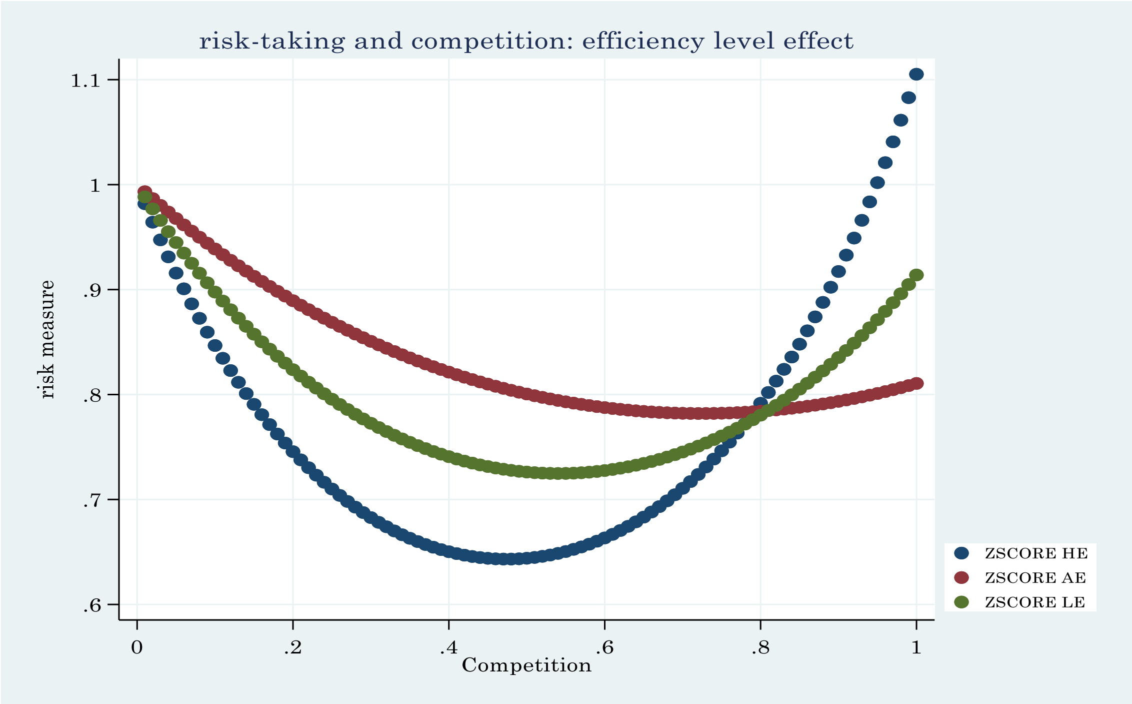


**Fig. 5.** Risk-taking and competition: Efficiency effect.

In terms of optimal value, highly efficient banks show the lowest value. As mentioned above, highly efficient banks may exhibit large values of bad loans because of skimping on cost for loan management while least efficient banks may suffer from poor management. Averagely efficient banks appear to be moderated as their level of market power increases.

*4.2.4. African CBB penetration and risk-taking*

As previously mentioned, African CBB has expanded across the African countries in the last decades. This section assesses how their market penetration affects risk-taking behaviour as in Wu et al. (2017). As reported in Table 9, our results suggest that ACBBs penetration induces banks to take less risk. Unlike Wu et al. (2017), African domestic banks seem to react more prudently when African CBBs penetrate their market. Also, our baseline results in Table 3 and Table 4 showed that African CBB take on average less risk than their counterparts.

Statistically, the effect is more significant when the proportion of African CBBs in terms of assets increases. However, the effect appears to be economically weak. For instance, a 10% increase in African CBBs share induces a 5% increase of the sample's average in the Z score for domestic banks. These results are different from those for emerging markets (Wu et al., 2017). The response of domestic banks to African's CBB is weak quantitatively. This may be mainly driven by the fact that African banking industries are still less competitive and the level of financial inclusion which is too low to stimulate market players to strongly react.

## 5. Sensitivity analysis and robustness checks

### *5.1. Different measures of competition, risk and efficiency*

We first employ the most recent used proxy of bank risk-taking, the loan growth rate (Dinger and te Kaat, 2020). As described before, this indicator assesses the extent to which banks take risk in growing their lending portfolio when competition increases. Foos et al. (2010) argued that banks may moderate their credit conditions due to a competitive environment in order to maintain their market share. An increase in lending induced by a relaxation of credit conditions expands the banks' exposure at default which is a risk-taking measure. In terms of credit growth proxy, we use the Abnormal loan growth rate ($ALGR_{it}$) which refers to the difference between the loan growth of a specific bank and the median of the country's aggregated loan growth. We also take into account efficiency level and cross-border banking in order to examine the stability of our results.

**Table 8**
NPLTA vs Competition: the effect of efficiency level.

| | (1) | (2) | (3) |
|---|---|---|---|
| Efficiency level | High | Average | Low |
| VARIABLES | $NPLTA_t$ | $NPLTA_t$ | $NPLTA_t$ |
| $NPLTA_{t-1}$ | 0.70601*** | 0.70742*** | 0.70519*** |
| | (0.00195) | (0.00319) | (0.00148) |
| $LIF_t$ | −0.95103** | −2.10943*** | −1.60633*** |
| | (0.37930) | (0.78799) | (0.43434) |
| ${LIF_t}^2$ | 2.97460*** | 5.65586*** | 5.75257*** |
| | (0.56078) | (1.23422) | (0.81390) |
| $LIF_t$ * *Efficiency level* | −0.73400 | 0.78764 | 0.69331 |
| | (0.70155) | (1.12713) | (1.06695) |
| ${LIF_t}^2$*Efficiency level* | 4.50045*** | −1.56698 | −2.27425 |
| | (1.13769) | (1.80790) | (1.66959) |
| *Efficiency level$_t$* | −0.38394*** | −0.04263 | 0.09712 |
| | (0.08823) | (0.15190) | (0.14453) |
| *African Cross* | −0.34295*** | −0.45255*** | −0.31973*** |
| | (0.07431) | (0.09506) | (0.07781) |
| $Liquid_t$ | −0.01657*** | −0.01818*** | −0.01723*** |
| | (0.00111) | (0.00184) | (0.00139) |
| $\log(SIZE)_t$ | −0.04780** | −0.06901** | −0.02064 |
| | (0.02392) | (0.03393) | (0.02515) |
| Constant | −1.51132 | 24.23189 | 14.40718 |
| | (15.05961) | (25.15292) | (12.95137) |
| Threshold | 0.11 | 0.16 | 0.13 |
| Hansen P-value | (0.515) | (0.776) | (0.398) |
| AB Residual test AR (1) | −3.64*** | −3.45*** | −3.60*** |
| AB Residual test AR (2) | (0.652) | (0.520) | (0.621) |
| Year dummy | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Observations | 1279 | 1279 | 1279 |
| Number of Banks | 240 | 240 | 240 |

This table reports a two-step system GMM estimation of the link between risk (here non-performing loan to total assets) and the Lerner index ($LIF_t$) considering the level of efficiency which higher (High) if its value is higher than the 3rd quartile, low is the value is lower (Low)than the 1rst quartile and medium (Average) otherwise. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

**Table 9**
African CBBs penetration and risk-taking.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | $lnZ_t$ | $NPLTA_t$ | $lnZ_t$ | $NPLTA_t$ |
| Panel A.1: Penetration in terms of number | | | Panel A.2: Penetration in terms of assets | |
| $RISK_{t-1}$ | 0.46091*** | 0.72522*** | 0.45125*** | 0.72529*** |
| | (0.03119) | (0.00145) | (0.03057) | (0.00143) |
| $LIF_t$ | 0.67896*** | −0.78684*** | 0.67928*** | −0.99403*** |
| | (0.13787) | (0.25670) | (0.13484) | (0.25685) |
| ${LIF_t}^2$ | −0.80809*** | 3.33725*** | −0.80545*** | 3.52732*** |
| | (0.19776) | (0.41709) | (0.19544) | (0.42603) |
| $ACBB_t$ | 0.00060 | −0.00457*** | 0.00071* | −0.00422*** |
| | (0.00043) | (0.00095) | (0.00039) | (0.00078) |
| Observations | 911 | 1276 | 911 | 1276 |
| Number of banks | 191 | 240 | 191 | 240 |
| Hansen P-value | (0.870) | (0.249) | (0.870) | (0.249) |
| AB Residual test AR (1) | −4.59*** | −3.09*** | −4.59*** | −3.09*** |
| AB Residual test AR (2) | (0.560) | (0.953) | (0.560) | (0.953) |
| Panel B.1: Penetration in terms of number | | | Panel B.2: Penetration in terms of assets | |
| $RISK_{t-1}$ | 0.24851*** | 0.79505*** | 0.24705*** | 0.79334*** |
| | (0.02222) | (0.00066) | (0.01945) | (0.00065) |
| $ACBB_t$ | 0.00075 | −0.00423*** | 0.00108** | −0.00166*** |
| | (0.00047) | (0.00054) | (0.00044) | (0.00046) |
| Hansen P-value | (0.760) | (0.880) | (0.743) | (0.901) |
| AB Residual test AR (1) | −2.56** | −2.17** | −2.55** | −2.17** |
| AB Residual test AR (2) | (0.760) | (0.661) | (0.628) | (0.660) |
| Observations | 417 | 573 | 417 | 573 |
| Number of banks | 90 | 108 | 90 | 108 |

This table disclosed a two-step GMM estimation results on the relationship between Bank risk and the penetration of African CBBs. Penetration is either measured by the proportion of African CBBs in the market. In Panels A.1 and A.2. we assess the effect of the penetration in the entire banking industry, while in panels B.1 and B.2, we only consider the reaction of domestic market to African CBBs' penetration ($ACBB_t$). Risk is measured by respectively the natural log of Z score $lnZ_t$ and the Nonperforming loan total assets ($NPLTA_t$). Standard errors are reported in parentheses, and ***, **, * denote statistical significance at level 1%, 5%, and 10%, respectively variables' definition is presented in Appendix 1.

**Table 10**
Loan growth and competition.

| | (1) | (2) | (3) |
|---|---|---|---|
| Level of Efficiency | High | Average | Low |
| VARIABLES | $ALGR_{it}$ | $ALGR_{it}$ | $ALGR_{it}$ |
| $ALGR_{it-1}$ | −0.01678*** | −0.02075*** | −0.01712*** |
| | (0.00241) | (0.00217) | (0.00224) |
| $PRH_t$ | 0.17031*** | 0.20616*** | 0.18835*** |
| | (0.05540) | (0.05785) | (0.05524) |
| $PRH_t^2$ | −0.15800** | −0.18191** | −0.17020** |
| | (0.07271) | (0.07541) | (0.07310) |
| Efficiency level | 0.02315*** | 0.00071 | −0.01770*** |
| | (0.00831) | (0.00413) | (0.00477) |
| *AfricanCross* | 0.09351*** | 0.09729*** | 0.09041*** |
| | (0.01085) | (0.01012) | (0.01003) |
| $Liquid_t$ | −0.00202*** | −0.00224*** | −0.00200*** |
| | (0.00017) | (0.00021) | (0.00021) |
| $\log(SIZE)_t$ | −0.05018*** | −0.05780*** | −0.05461*** |
| | (0.00650) | (0.00619) | (0.00659) |
| $DIV_t$ | 0.00361*** | 0.00358*** | 0.00360*** |
| | (0.00007) | (0.00015) | (0.00018) |
| $GOV_t$ | 0.02126*** | 0.02399*** | 0.02001*** |
| | (0.00397) | (0.00392) | (0.00401) |
| $INFL_t$ | 0.00614*** | 0.00614*** | 0.00614*** |
| | (0.00031) | (0.00034) | (0.00034) |
| $FINDEV_t$ | 0.00027* | 0.00022** | 0.00042*** |
| | (0.00014) | (0.00011) | (0.00007) |
| $GDPgrowht_t$ | 0.00117** | 0.00204*** | 0.00190*** |
| | (0.00048) | (0.00046) | (0.00047) |
| $GDPgrowth_{t-1}$ | 0.03270*** | 0.03259*** | 0.03224*** |
| | (0.00047) | (0.00051) | (0.00048) |
| Thresholds | 0.53 | 0.57 | 0.55 |
| Hansen *P*-value | (0.151) | (0.154) | (0.143) |
| AB Residual test AR (1) | −1.80*** | −1.79*** | −1.80*** |
| AB Residual test AR (2) | (0.973) | (0.995) | (0.962) |
| Observations | 1185 | 1185 | 1185 |
| Number of Banks | 168 | 168 | 168 |

This table discloses the two-step GMM estimation results related to the link between the abnormal loan growth ($ALGR_{it}$) and the competition ($PRH_t$). The Abnormal loan growth rate is computed by the difference between the loan growth of a specific bank and the median of the country's aggregated loan growth. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at level 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

**Table 11**
Risk vs competition: does efficiency matter.

| Panel A: Lerner Index as a competition proxy | | | |
|---|---|---|---|
| Efficiency level | High | Average | Low |
| | (1) | (2) | (3) |
| VARIABLES | $\sigma_{ROAt}$ | $\sigma_{ROAt}$ | $\sigma_{ROAt}$ |
| $lnZ_{t-1}$ | 0.24310*** | 0.48849*** | 0.22514*** |
| | (0.00612) | (0.00888) | (0.00696) |
| $LIF_t$ | −1.99967*** | −1.75338*** | −0.44007* |
| | (0.54175) | (0.32991) | (0.23222) |
| $LIF_t^2$ | 3.06717** | 3.71616*** | 0.75265* |
| | (1.08387) | (0.51406) | (0.39376) |
| *Effficiency level* | −0.42427*** | 1.43424** | |
| | (0.09368) | (0.43635) | |
| $LIF_t$ * *Effficiency level* | 2.87066*** | 1.43424** | −2.88876** |
| | (0.72507) | (0.43635) | (1.42213) |
| $LIF_t^2$**Efflevel* | −3.62897** | −3.42862*** | 5.65894** |
| | (1.26418) | (0.64567) | (2.81572) |
| *African Cross* | −0.13137** | −0.07413** | −0.13714** |
| | (0.04595) | (0.03141) | (0.04977) |
| Threshold | 0.78 | 0.31 | 0.26 |
| Hansen P-value | (0.775) | (0.530) | (0.373) |
| AB Residual test AR (1) | −2.20** | −1.95* | −2.22** |
| AB Residual test AR (1) | (0.275) | (0.186) | (0.220) |
| Year dummy | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Observations | 1250 | 1250 | 1250 |
| Number of Banks | 243 | 243 | 243 |
| | | | |
| Panel B: Panzar-Ross as a competition proxy. | | | |
| VARIABLES | $\sigma_{ROAt}$ | $\sigma_{ROAt}$ | $\sigma_{ROAt}$ |
| $RISK_{t-1}$ | 0.35825*** | 0.35831*** | 0.37174*** |
| | (0.00180) | (0.00339) | (0.00325) |
| $PRH_t$ | 1.83409*** | 0.75588* | 3.30703*** |
| | (0.29572) | (0.42024) | (0.23394) |
| $PRH_t^2$ | −1.59858*** | −0.81394** | −3.00164*** |
| | (0.27739) | (0.39729) | (0.21123) |
| $PRH_t$ * *Efficiency Level* | 1.45069*** | 0.88920** | −11.34919*** |
| | (0.25146) | (0.35328) | (0.43244) |
| $PRH_t^2$**Efficiency Level* | −1.49470*** | −0.57454* | 10.28317*** |
| | (0.24784) | (0.33679) | −11.34919*** |
| *Efficiency Level*$_t$ | −0.46948*** | −0.21406*** | 2.80941*** |
| | (0.05293) | (0.07765) | (0.08756) |
| $ACBB_t$ | −0.00109*** | −0.00034 | −0.00054 |
| Threshold | 0.53 | 0.59 | 0.55 |
| Hansen P-value | (0.433) | (0.969) | (0.176) |
| AB Residual test AR (1) | −2.16** | −2.17** | −2.15** |
| AB Residual test AR (2) | (0.109) | (0.122) | (0.116) |
| Year Dummy | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Observations | 859 | 859 | 859 |
| Number of Banks | 136 | 136 | 136 |

This table reports a two-step system GMM estimation of the link between risk (standard deviation of the return on assets ($\sigma_{ROAt}$) and the Lerner index ($LIF_t$) as computed from the Fourier flexible SFA considering the level of efficiency which higher (High) if its value is higher than the 3rd quartile, low is the value is lower (Low) than the 1rst quartile and Average (Average) otherwise. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

As presented in Table 10, the results suggests that high and average efficient banks increase their exposure at default when competition increases. More efficient banks may take high risk because of the low loan interest rate they are able to offer. However, less efficient banks might increase their exposition to risk in order to compensate the drop of market share or market power induced by the increase in competition. Averaged efficient banks show more prudent behaviour in risk-taking as confirmed in our previous analyses.

Second, we further examine this relationship in measuring risk by the standard deviation of the return on assets. A high standard deviation implies high risk, and a positive sign associated with any covariate will suggest that its marginal increase will rise the bank's risk level. As reported in Table 11, results across all the regressions suggest the persistence of the risk measure.

As in the previous results, our estimations support the nonlinear relationship between competition and bank-risk taking in Africa. The thresholds of market power are, respectively, 0.78, 0.31 and 0.26 for most, averagely and least efficient and 0.53, 0.59 and 0.55

**Table 12**
Number banks vs. risk.

| | Panel A: Number of banks vs. risk ($lnZ_t$) | | | Panel B: Number of banks vs. risk $NPLTA_t$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) |
| Efficiency Level | High | Average | Low | High | Average | Low |
| VARIABLES | $lnZ_t$ | $lnZ_t$ | $lnZ_t$ | $NPLTA_t$ | $NPLTA_t$ | $NPLTA_t$ |
| $RISK_{t-1}$ | 0.24281*** | 0.25049*** | 0.27410*** | 0.57066*** | 0.66166*** | 0.57350*** |
| | (0.00803) | (0.00860) | (0.00834) | (0.00134) | (0.00054) | (0.00115) |
| $n_t$ | −0.02963*** | −0.01723*** | −0.02902*** | 0.01977* | 0.01158** | −0.02152** |
| | (0.00237) | (0.00215) | (0.00255) | (0.01057) | (0.00475) | (0.00924) |
| $n_t^2$ | 0.00095*** | 0.00050*** | 0.00093*** | −0.00133*** | −0.00046*** | 0.00041 |
| | (0.00011) | (0.00011) | (0.00011) | (0.00041) | (0.00017) | (0.00035) |
| $n_t$ * *Efficiency level* | 0.02296*** | −0.01528*** | 0.01904*** | −0.06066*** | −0.02329*** | 0.10516*** |
| | (0.00306) | (0.00255) | (0.00676) | (0.01859) | (0.00431) | (0.01707) |
| $n_t^2$*Efficiency level* | −0.00083*** | 0.00055*** | −0.00082*** | 0.00241*** | 0.00063*** | −0.00454*** |
| | (0.00014) | (0.00012) | (0.00031) | (0.00073) | (0.00016) | (0.00078) |
| *Efficiency level*$_t$ | −0.07872*** | 0.06873*** | −0.12044*** | 0.52438*** | −0.01308 | −0.53667*** |
| | (0.01523) | (0.01159) | (0.03268) | (0.08520) | (0.02679) | (0.07124) |
| Constant | 6.64342*** | 6.69132*** | 6.43530*** | 190.16581*** | 154.91549*** | 197.70493*** |
| | (2.05822) | (1.90337) | (1.77208) | (6.68949) | (4.31469) | (8.31437) |
| Hansen P-value | (0.491) | (0.495) | (0.405) | (0.590) | (0.606) | (0.744) |
| AB Residual test AR (1) | −5.34*** | −5.36*** | −5.45*** | −1.80* | −1.79* | −1.81* |
| AB Residual test AR (2) | (0.133) | (0.134) | (0.192) | (0.432) | (0.416) | (0.427) |
| Observations | 1295 | 1295 | 1295 | 1801 | 1801 | 1801 |
| Number of Banks | 244 | 244 | 244 | 287 | 287 | 287 |

This table reports a two-step system GMM estimation of the link between risk and the number of banks in the market as a competition proxy. Derived from Fourier flexible SFA considering the level of efficiency which higher (High) if its value is higher than the 3rd quartile, low is the value is lower (Low) than the 1rst quartile and Average (AE) otherwise. Supervisory power, information sharing, and the lags of the dependent variable are used as instruments. In Panel A, the risk is measured by the *Z*-score logarithm, while in Panel B, by a Non-performing loan to total assets. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

when competition is measured by the Panzar-Ross continuous-time curve. Regarding the coefficients, averagely efficient banks take less risk compared to their peers as in the baseline findings.

Third, like Anginer et al. (2014), we explore the relationship between the number of banks in the market and the risk. According to Bikker and Haaf (2002), the number of banks can be used as a proxy of competition, because generally, higher number of banks in the market implies greater competition. The related results are disclosed in Table 12 and display similar findings to those in the baseline regression. They corroborate a nonlinear relationship between competition and risk while accounting for the role of efficiency in bank risk-taking.

Fourth, we further explore the sensitivity of our baseline results by employing different measures of Z-score. First, we extend the time window for the computation of the Z-score. Unlike the Z-score that we have used in the baseline regression and which was determined based on a 3-year rolling window, we compute a new Z score for a 5-year rolling-window. Second, we use two modified $Z_{it}$ scores. The first is a normalised $Z_{it}$ score that is computed as follows: for each country, we calculated the maximum and the minimum values of $Z_{it}$. Then, we normalise the value using the following equation:

$$\frac{Z_{it} - minZ_{tj}}{maxZ_{it} - minZ_{tj}} \tag{20}$$

The second, is derived from a stochastic frontier with the idea of comparing the actual value to the maximum possible value of Z (Chen et al., 2017; Tabak et al., 2012; Wu et al., 2017). In terms of interpretation a higher score implies less risk-taking by banks since it indicates how close the bank is to the most possible maximum solvency. The value is derived from Eq. (10) with the only difference that the dependent variable is the Z score.

As shown in Table 13, the relationship between the Z score's normalised value to the competition is similar to the baseline regression. Moreover, the findings corroborate the importance of bank efficiency in the relationship between competition and risk-taking. We also find that the change of time window does not affect the stability of our results. As in the baseline regression, the thresholds for a 5-year rolling window are respectively 0.34, 0.72 and 0.58 for high, average and low efficiency.

### 5.2. Further robustness checks

We follow Chen et al. (2017)'s strategy to implement a panel logit regression. We argue that a bank with a lower Z score is more exposed to default. We define a threshold from the first quartile ($Q_{0.25}$) as the value below which a bank is more exposed to failure. Therefore, our dependent variable takes 1 if $Q_{0.25} < Z_{it}$ and 0 otherwise. Then a regression is performed using the following equation:

**Table 13**
Different Z score measures.

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | $Norm\_lnZ_{it}$ | $lnZ_{it}(5years)$ | $SFAlnZ_{it}$ |
| $RISK_{t-1}$ | 0.57128*** | 0.40772*** | 0.83552*** |
| | (0.03024) | (0.02680) | (0.03006) |
| $CE_t$ | 0.03570* | 0.07992*** | 0.02220 |
| | (0.02038) | (0.02099) | (0.03224) |
| Constant | 4.47769*** | −13.20291*** | −8.76709*** |
| | (1.50474) | (1.76205) | (2.55301) |
| Controls | Yes | Yes | Yes |
| Hansen P-value | (0.174) | (0.234) | (0.722) |
| AB Residual test AR (1) | −4.68*** | −5.25*** | −4.30*** |
| AB Residual test AR (2) | (0.645) | (0.360) | (0.445) |
| Observations | 908 | 1118 | 803 |
| Number banks | 191 | 224 | 179 |

This table reports an estimation of the relationship between Risk and competition measures. We use three modified Z scores, and the first is a normalised Z score Column (1), the second in the Z-score computed in terms of efficiency Column (2), and a 5-year rolling window for the computation of Z score Column (3). Standarderrors are reported in parentheses, and ***, **, * denote statistical significance at level 1%, 5%, and 10%, respectively variables' definition is presented in Appendix 1.

$$Pr\left(D_{it} = 1_{(Q_{0.25}<Z)}\right) = \Phi\left(\alpha_0 + \alpha_1 COMP_k + \sum_{i=1}^{k}\beta_i X_{it} + \sum_{i=j}^{q}\delta_j F_{jt} + \mu_i + \varepsilon_{it}\right) \tag{21}$$

**Table 14**
Logit estimation risk vs. competition.

| | Panel A.1: Logit random effect estimation | | | Panel A.2: Probit Random Effect estimator | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) |
| | High | Average | Low | High | Average | Low |
| VARIABLES | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ |
| $LIF_t$ | −7.62608*** | −7.59559*** | −7.76505*** | −4.25871*** | −4.25226*** | −4.33425*** |
| | (2.27113) | (2.26076) | (2.24974) | (1.26363) | (1.26020) | (1.25259) |
| ${LIF_t}^2$ | 7.07031** | 7.35912** | 7.76152** | 3.96208** | 4.13190** | 4.34642** |
| | (3.47056) | (3.44553) | (3.43360) | (1.94006) | (1.92591) | (1.91541) |
| $Efficiencylevel_t$ | 0.57753* | −0.44242* | 0.13349 | 0.31974* | −0.24604* | 0.07366 |
| | (0.30370) | (0.23969) | (0.30767) | (0.17130) | (0.13551) | (0.17426) |
| $Liquid_t$ | −0.00486 | −0.00646 | −0.00635 | −0.00261 | −0.00352 | −0.00349 |
| | (0.00855) | (0.00851) | (0.00847) | (0.00478) | (0.00476) | (0.00474) |
| $\log(SIZE)_t$ | −0.21523* | −0.23263** | −0.24376** | −0.12247** | −0.13219** | −0.13887** |
| | (0.11047) | (0.10827) | (0.10671) | (0.06192) | (0.06075) | (0.05995) |
| $DIV_t$ | 0.02193** | 0.02110** | 0.02019** | 0.01193** | 0.01137** | 0.01093** |
| | (0.00937) | (0.00929) | (0.00922) | (0.00522) | (0.00517) | (0.00514) |
| *Constant* | −0.83410 | −0.38567 | −0.64584 | −0.43981 | −0.17501 | −0.32828 |
| | (1.56487) | (1.54995) | (1.52437) | (0.87509) | (0.86866) | (0.85414) |
| $LR\ \chi^2 test$ | 99.47*** | 98.27*** | 95.96*** | 104.02*** | 106.66*** | 100.98*** |
| Wald test | 52.10*** | 52.60*** | 51.10*** | 54.05 | 54.31*** | 52.81*** |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1123 | 1162 | 1162 | 1113 | 1113 | 1113 |
| Number of banks | 182 | 183 | 183 | 182 | 182 | 182 |
| Panel B.1: Logit random effect estimation | | | | Panel B.2: Probit Random Effect | | |
| Efficiency Level | High | Average | Low | High | Average | Low |
| VARIABLES | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ | $P(D = 1/ \ int\ Z_t < Z_{0.25}$ |
| $PRH_t$ | 11.45855*** | 11.47284*** | 11.34992*** | 6.27946*** | 6.25818*** | 6.16973*** |
| | (3.97189) | (4.02517) | (4.01906) | (2.25195) | (2.28352) | (2.27822) |
| ${PRH_t}^2$ | −10.38393*** | −10.56730*** | −10.44437*** | −5.66356*** | −5.74247*** | −5.65851*** |
| | (3.70373) | (3.75439) | (3.74974) | (2.09989) | (2.13006) | (2.12636) |

(continued on next page)

**Table 14** (continued)

| | Panel A.1: Logit random effect estimation | | | Panel A.2: Probit Random Effect estimator | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) |
| | High | Average | Low | High | Average | Low |
| VARIABLES | $P(D=1/\ int\ Z_t < Z_{0.25}$ | $P(D=1/\ int\ Z_t < Z_{0.25}$ | $P(D=1/\ int\ Z_t < Z_{0.25}$ | $P(D=1/\ int\ Z_t < Z_{0.25}$ | $P(D=1/\ int\ Z_t < Z_{0.25}$ | $P(D=1/\ int\ Z_t < Z_{0.25}$ |
| $Efficiencylevel_t$ | −0.47358** | 0.23273 | 0.10087 | −0.26284** | 0.12700 | 0.06324 |
| | (0.22782) | (0.17973) | (0.22560) | (0.13009) | (0.10378) | (0.13018) |
| *Constant* | −1.73589 | −2.03605* | −1.91045* | 6.27946*** | 6.25818*** | 6.16973*** |
| | (1.13961) | (1.15511) | (1.14797) | (2.25195) | (2.28352) | (2.27822) |
| $LR\ \chi^2 test$ | 151.44*** | 163.13*** | 160.01*** | 153.43*** | 165.19*** | 162.17*** |
| Wald test | 38.58*** | 35.38*** | 34.22*** | 38.65*** | 35.46*** | 34.50*** |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1339 | 1339 | 1339 | 1339 | 1339 | 1339 |
| Number of banks | 183 | 183 | 183 | 183 | 183 | 183 |

This table presents a logit panel fixed and random effects approach estimations. We defined the Z variable's last quartile as the threshold from which the bank is more likely to default. The dependent variable takes 1 is the Z of the bank lies under the first quartile and 0 otherwise. Panel A presents Logit random related results, and Panel B Probit random effect results. Standard are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

**Table 15**
Competition vs. risk: Size effect.

| | (1) | (2) | (3) |
|---|---|---|---|
| | SMALL | MEDIUM | BIG |
| VARIABLES | $NPLTA_t$ | $NPLTA_t$ | $NPLTA_t$ |
| $NPLTA_{t-1}$ | 0.71994*** | 0.72056*** | 0.72119*** |
| | (0.00061) | (0.00073) | (0.00073) |
| $LIF_t$ | −1.53043*** | −0.82404*** | −2.60325*** |
| | (0.13843) | (0.28729) | (0.17223) |
| ${LIF_t}^2$ | 5.04589*** | 2.43265*** | 6.72110*** |
| | (0.28040) | (0.64387) | (0.32809) |
| $LIF_t * Size$ | 0.64761 | −1.42229*** | 2.55281*** |
| | (0.81792) | (0.35180) | (0.42459) |
| ${LIF_t}^2 * Size$ | −3.21958* | 4.24025*** | −5.32211*** |
| | (1.66219) | (0.69904) | (0.67051) |
| $Size_t$ | 0.42127*** | −0.16452*** | −0.19158*** |
| | (0.07154) | (0.03672) | (0.04203) |
| $CE_t$ | −0.27683*** | −0.30460*** | −0.30057*** |
| | (0.08734) | (0.08769) | (0.09014) |
| Constant | 37.60347*** | 50.80737*** | 55.36438*** |
| | (5.81727) | (6.19747) | (6.55126) |
| Hansen P-value | (0.728) | (0.749) | (0.747) |
| AB Residual test AR (1) | −2.90*** | −2.86*** | −2.86*** |
| AB Residual test AR (2) | (0.556) | (0.543) | (0.525) |
| Observations | 1539 | 1539 | 1539 |
| Number of Banks | 274 | 274 | 274 |

This table disclosed two-step GMM estimation results about Bank risk and competition measured by the Lerner Index ($LIF_t$). Legal Origin takes value 1 if the bank is from English common-law and 0 otherwise. We split the sample into three categories, respectively Big with a size larger than the third quartile, medium with size comprised between the first and the third quartile, and small size lower than the first quartile. Standard robust errors are reported in parentheses, and ***, **, * denote statistical significance at levels 1%, 5%, and 10%, respectively. Variables' definition is presented in Appendix 1.

where $D_{it}$ stands for the risk of bank $i$ and time $t$, and other variables stand for the same as in Eq. (18), the baseline regression. Results regarding this analysis are reported in Table 14.

Results are similar to the baseline findings and keep supporting the nonlinear relationship between market power and risk. High market power (less competition) is associated with a lower probability of insolvency until the optimal value above which a marginal increase in market power or in competition exposes the bank to the risk of default or to less default probability. While the least efficient banks increase the probability of default, averagely efficient banks show resilience to default, although their effect is statistically insignificant when competition is measured by $PRH_t$. Similarly, most efficient banks show lower probability of default when competition increases.

We further investigate the role of size in the relationship between the two covariates. Like Tabak et al. (2012), we split our sample

**Table 16**
Competition vs Riskiness: accounting for legal origin.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | $lnZ_t$ | $NPLTA_t$ | $lnZ_t$ | $NPLTA_t$ |
| $RISK_{t-1}$ | 0.45346*** | 0.71783*** | 0.23005*** | 0.97038*** |
| | (0.03148) | (0.00151) | (0.00170) | (0.00358) |
| $LIF_t$ | 0.66481*** | −0.91770*** | | |
| | (0.13752) | (0.25231) | | |
| $LIF_t^2$ | −0.75215*** | 3.23617*** | | |
| | (0.20269) | (0.42501) | | |
| $PRH_t$ | | | −1.05504*** | 2.14533*** |
| | | | (0.08897) | (0.73064) |
| $PRH_t^2$ | | | 0.95196*** | −1.54080** |
| | | | (0.08151) | (0.64722) |
| *AfricanCross* | 0.07280*** | −0.40538*** | 0.00121*** | −0.00818*** |
| | (0.01767) | (0.05239) | (0.00005) | (0.00070) |
| $\log(SIZE)_t$ | 0.04681*** | −0.09213*** | 0.08298*** | −0.55031*** |
| | (0.00970) | (0.01724) | (0.00212) | (0.03736) |
| *LEGALO* | 0.05757* | −0.32785*** | 0.04295*** | −0.17479*** |
| | (0.03093) | (0.04355) | (0.00587) | (0.01243) |
| Constant | 1.26465 | 72.13815*** | 20.05108*** | 102.12091*** |
| | (5.87088) | (13.60536) | (0.69410) | (8.48271) |
| Hansen P-value | (0.882) | (0.303) | (0.663) | (0.737) |
| AB Residual test AR (1) | −4.63*** | −3.08*** | −4.39*** | −3.66*** |
| AB Residual test AR (2) | (0.671) | (0.922) | (0.343) | (0.419) |
| Observations | 911 | 1276 | 805 | 739 |
| Number of Banks | 191 | 240 | 132 | 130 |

This table disclosed a two-step GMM estimation result on the relationship between Bank risk and competition. Competition is measure by Lerner Index ($LIF_t$) and risk by respectively the natural log of Z score $lnZC_t$ and the Nonperforming loan total assets $NPLTA_t$. Legal Origin takes value 1 if the bank is from English common-law and 0 otherwise. Standard robust errors are reported in parentheses, and ***, **, * denote statistical significance at level 1%, 5%, and 10%, respectively variables' definition is presented in Appendix 1.

into three categories, respectively large, medium, and small size banks. We investigate whether the size effect on a bank's risk-taking behaviour varies across different size categories.

As reported in Table 15, our results show that bank's size matters as in Tabak et al. (2012). We find differences in relationships between competition and risk conditional to bank size. While large and medium banks tend to exhibit lower risk below the optimal value, small banks, tend to take less risk when their market power converges toward 1. In the market power-fragility part of the relationship, medium size banks tend to exhibit high values of $NPLTA_t$. Because market power is the opposite of market competition, our results are similar to those of Tabak et al. (2012), which suggests that large banks tend to cope with competition compared to small and medium banks.

Overall, our results support the importance of size in the analysis of risk-taking behaviour and the importance of splitting the sample in terms of efficiency to unveil the real effect of competition on a bank risk-taking behaviour.

We further account for legal origin to evaluate the difference between English common law and Civil law in terms of a bank risk-taking. We follow Porta et al. (1998), who argued that common law origin banking systems offer more advantages in terms of investment opportunities and regulations than others. We use a dummy variable that takes 1 if the banking system is from Common-law origin and 0 if otherwise. Results disclosed in Table 16 suggest that common-law origin banks are less exposed to risk-taking than their counterparts. A possible explanation could be that common-law origin offers more legal protections to banks and consequently should have more regulated banking systems in terms of capital requirement, and information sharing(seeTable 17)

We also explore the effect of the financial crisis during 2008. The financial crisis variable (Crisis) takes value 1 during 2008–2009 and 0 otherwise. We show that the financial crisis positively impacted the risk-taking by decreasing bank's solvency and increasing bad loans.

Although cost efficiency is the best measure of management quality (Assaf et al., 2019), we explore how profit efficiency affects the relationship between risk and competition. Profit efficiency can affect risk-taking either through high risk-taking or the charter value channel. High profits may be generated from risky assets, which might affect the risk-taking of the bank. As presented in Table 18, results show that high profit efficiency is associated with high insolvency supporting the risk-taking channel (risky activities are associated with high profits). Conversely, the results show a negative relationship between profit efficiency and nonperforming loans. A possible explanation could be that, while maximising their profit, banks decide on the quantity of loans to grant rather than raising interest rates. That could incidentally affect the quality of loans.

**Table 17**
Crisis Effect.

| | (1) | (2) |
|---|---|---|
| Panel A: Crisis effect | | |
| VARIABLES | $lnZC_t$ | $NPLTA_t$ |
| $RISK_{t-1}$ | 0.45774*** | 0.71816*** |
| | (0.03243) | (0.00152) |
| $LIF_t$ | 0.68954*** | −0.90089*** |
| | (0.14073) | (0.25140) |
| $LIF_t^2$ | −0.78679*** | 3.31893*** |
| | (0.20706) | (0.42303) |
| crisis | −0.00503 | 0.09583*** |
| | (0.02228) | (0.02871) |
| Constant | 0.44919 | 66.94240*** |
| | (6.82969) | (13.57782) |
| Observations | 911 | 1276 |
| Number of banks | 191 | 240 |
| Hansen *P*-value | (0.868) | (0317) |
| AB Residual test AR (1) | −4.63*** | −3.07*** |
| AB Residual test AR (2) | (0.721) | (0.921) |

This table discloses a two-step GMM estimation results on the relationship between Bank risk and competition by accounting for the financial crisis period. Competition is measured by the Lerner Index ($LIF_t$) and risk by respectively the natural log of Z score $lnZC_t$ and the Nonperforming loan total assets $NPLTA_t$. The financial crisis (Crisis) takes value 1 during 2008–2009 and z and 0 otherwise. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at level 1%, 5%, and 10%, respectively variables' definition is presented in Appendix 1.

Another possible explanation is that while banks may grant loans at relatively high interest rates, they might cherry-pick customers whose probability of default is relatively low. Finally, the results suggest that profit efficiency interactions terms are statistically significant supporting the moderating effect of profit efficiency of banks when competition grows.

## 6. Conclusion

In this study, we investigated whether there is a difference in risk-taking behaviour between most and least efficient banks when competition increases in the banking industry. We also emphasise the effect of African cross-border banking, which has induced increased competition in the African banking industry. To that end, we modified the Martinez-Miera and Repullo (2010)'s specification by accounting for heterogeneous efficiency among banks. Our results suggest the importance of efficiency both for intermediary and recovery costs. The study shows a negative relationship between cost efficiency and the probability of bank failure. It also suggests that cost efficiency can moderate the effect of competition on risk-taking in nonlinear framework.

A sample of 430 African commercial banks is used to investigate our research question. It is split into banks with high, average, and low efficiency respectively for efficiency levels higher than the third quartile, between the first and third quartile, and less than the first quartile.

Our results support a nonlinear relationship between competition-risk-taking behaviour, suggesting the coexistence of competition-fragility (market power-stability) and competition-stability (market power-fragility) hypothesis. On top of supporting the moderating effect of cost efficiency in the nonlinear relationship between competition and efficiency, this study reveals that bank risk-taking differs across efficiency levels when competition increases. It shows that averagely efficient banks tend to react more prudently than most and least efficiency banks. While more efficient banks risk-taking may be related to costs' skimping, the least efficient banks seem to be more fragile due to bad management. Among additional controls, size, diversification index, macroeconomic and institutional variables show significant effects in the risk-taking behaviour.

Because this study considers the ownership structure in the relationship between competition and risk-taking behaviour, our results suggest that African cross-border banks are stability drivers because they take less risk than their peers. Moreover, we found that the expansion of African CBBs decrease the risk-taking of domestic banks in the host's country. However, in the long-run, this could be harmful to the financial stability because we find that above a certain threshold of competition, domestic and other foreign banks would tend to take more risks probably as a result of relaxing their credit conditions. Finally, our results show that the financial crisis is associated with high risk-taking in the banking industry.

In terms of policy implication, bank managers have to moderate their level of efficiency since excessive cost efficiency may be induced by costs' skimping which can incidentally affect the loan management performance. African countries should encourage cross-border banks' penetration by improving institutional quality that are the main drivers of financial development and stability. Besides, an emphasis should be made on regulatory frameworks by adopting more stringent regulation policies that allow hindering banks from

**Table 18**
Competition and risk: the profit efficiency effect.

| Panel A: Direct effect of profit efficiency | | |
|---|---|---|
| | (1) | (2) |
| VARIABLES | $lnZC_{it}$ | $NPLTA_{it}$ |
| $RISK_{it-1}$ | 0.20308*** | 0.75316*** |
| | (0.00949) | (0.00907) |
| $PRH_t$ | −0.54583** | 2.73024** |
| | (0.20587) | (0.94651) |
| $PRH_t{}^2$ | 0.51442** | −2.44612** |
| | (0.18754) | (0.83373) |
| $PROEF_{it}$ | −0.21910** | −0.56238*** |
| | (0.06517) | (0.14924) |
| Constant | 19.20855*** | 83.04574*** |
| | (2.43278) | (6.23265) |
| Hansen *P*-value | (0.313) | (0.622) |
| AB Residual test AR (1) | −4.15*** | −3.50*** |
| AB Residual test AR (2) | (0.242) | (0.222) |
| Observations | 805 | 739 |
| Number of Banks | 132 | 130 |

| Panel B: Profit efficiency as a moderating factor | | |
|---|---|---|
| | (1) | (2) |
| VARIABLES | $lnZC_{it}$ | $NPLTA_{it}$ |
| $RISK_{it-1}$ | 0.20628*** | 0.76522*** |
| | (0.01056) | (0.00774) |
| $PRH_t$ | 1.73847 | 0.25328*** |
| | (1.34768) | (0.03548) |
| $PRH_t{}^2$ | −1.90034 | −0.22941*** |
| | (1.16173) | (0.03157) |
| $PROEF_{it}$ * $PRH_t$ | −3.12195 | −0.30969*** |
| | (1.97136) | (0.04882) |
| $PROEF_{it}$*$PRH_t{}^2$ | 3.29665* | 0.28169*** |
| | (1.69207) | (0.04317) |
| $PROEF_{it}$ | 0.35419 | 0.06656*** |
| | (0.52977) | (0.01263) |
| Constant | 20.85786*** | 0.83234*** |
| | (2.58256) | (0.06370) |
| Hansen P-value | (0.313) | (0.622) |
| AB Residual test AR (1) | −4.15*** | −3.50*** |
| AB Residual test AR (2) | (0.242) | (0.222) |
| Observations | 805 | 739 |
| Number of Banks | 132 | 130 |

This table discloses two-step GMM estimation results on the relationship between Bank risk and competition. Competition is measured by $PRH_t$ and risk by respectively the natural log of Z score $lnZC_{it}$ and the Nonperforming loan total assets $NPLTA_{it}$. Efficiency is measured by $PROEF_{it}$, the profit efficiency score. Standard errors are reported in parentheses, and ***, **, * denote statistical significance at level 1%, 5%, and 10%, respectively variables' definition is presented in Appendix 1.

taking excessive risks. Most importantly, the adoption of some Basel 2.5 and Basel 3 recommendations would enhance the stability of African banking industry by limiting the risk-taking by banks.

## Funding

The authors thank the financial support recieved from Brot Für Die Welt (Pain Pour Le Monde) and Université Evangélique en Afrique (U.E.A/Bukavu) through the project “Improvement of research and teaching quality” (Projet-A-COD-2018-0383).

## CRediT authorship contribution statement

**Luc Matabaro Borauzima:** Conceptualization, Methodology, Formal analysis, Data curation, Visualization. **Aline Muller:** Conceptualization, Validation, Formal analysis, Project administration, Supervision.

## Declaration of Competing Interest

The authors declare no competing interests.

## Appendix 1 Variables definition

| Variables | Description | Source |
|---|---|---|
| Risk-measures | | |
| $\sigma_{ROA}$ | Standard Deviation of the return of assets on a 3-year time window | Authors' calculations |
| $lnZC_t$ | *Z*-score is the ratio of the sum of the average of ROA and capital ratio to the standard deviation of ROA | Authors' calculations |
| $NPLTA_t$ | Is the ratio of Non-performing over total assets | Bankscope |
| $\boldsymbol{CE_t}$ | Cost efficiency score obtained by dividing the profit of bank i by the maximum bank profit. The score is computed using a Fourier Flexible Stochastic Frontier function. | Author's own calculation using Bankscope Data |
| Independent variable | | |
| *Market structure related variables* | | |
| $LIF_t$ | Describes the market power of a given bank at time t derived from the Fourier Flexible cost function with single output. It is the ratio of the price to cost margin over the price | Author's own calculation using Bankscope Data |
| $PRH_t$ | $PRH_t$statistics is set such that, $PRH_t < 0$ corresponds to a monopolistic market, $PRH_t = 1$ refers to perfect competition and $0 < PRH_t < 1$ for monopolistic competition. | Author's own calculation using Bankscope Data |
| *Bank specific variables* | | |
| $Liquid_t$ | It is measured by the ratio of liquid assets over the total assets | Bankscope |
| $\log(SIZE)_t$ | The natural log of total assets | Bankscope |
| $DIV_t$ | Income diversification is computed as the ratio of non-interest income over the total operating income | Bankscope |
| *Macroeconomic variables and Financial development indicator* | | |
| $GDPgrowht_t$ | Yearly GDP growth rate in % | World development indicators |
| $INFL_t$ | Yearly consumer price index variable in percentage % | World development indicators |
| $FINDEV_t$ | Private credit by deposit money banks and other financial institutions to GDP, calculated using the following deflation method based on the consummer price index. Raw data are from the electronic version of the IMF's International Financial Statistics. | Global financial development |
| Institutional variables | | |
| Control of Corruption: | Control of Corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. | Word Governance Indicators |
| Political Stability and Absence of Violence/Terrorism: | Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator | Word Governance Indicators |
| Government Effectiveness: | Government Effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. | Word Governance Indicators |
| Regulatory Quality: | Regulatory Quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the WGI. | Word Governance Indicators |
| Legal origin | It is a dummy variable which takes 1 if the bank is located in a country where English Common-law is applied or 0 otherwise. | Porta et al. (1998) |

## Appendix 2 Sample's distribution across countries

| N° | COUNTRY | FCBB | ACBB | CBB | DOM | Total |
|---|---|---|---|---|---|---|
| 1 | Algeria | 5 | 0 | 5 | 12 | 17 |
| 2 | Angola | 0 | 1 | 1 | 12 | 13 |
| 3 | Benin | 0 | 6 | 6 | 2 | 8 |
| 4 | Botswana | 1 | 1 | 2 | 2 | 4 |
| 5 | Burkina Faso | 1 | 6 | 7 | 2 | 9 |
| 6 | Burundi | 0 | 1 | 1 | 5 | 6 |
| 7 | Cameroon | 3 | 4 | 7 | 5 | 12 |
| 8 | Cape Verde | 0 | 2 | 2 | 4 | 6 |
| 9 | Central African Republic | 0 | 1 | 1 | 1 | 2 |
| 10 | Guinea | 0 | 5 | 5 | 1 | 6 |
| 11 | Ivory Coast | 2 | 5 | 7 | 5 | 12 |
| 12 | Djibouti | 0 | 3 | 3 | 2 | 5 |
| 13 | DR Congo | 2 | 7 | 9 | 5 | 14 |
| 14 | Egypt | 2 | 3 | 5 | 15 | 20 |
| 15 | Ethiopia | 1 | 3 | 4 | 8 | 12 |
| 16 | Gabon | 0 | 3 | 3 | 2 | 5 |
| 17 | Gambia | 4 | 2 | 6 | 0 | 6 |

(continued on next page)

(*continued*)

| N° | COUNTRY | FCBB | ACBB | CBB | DOM | Total |
|---|---|---|---|---|---|---|
| 18 | Ghana | 4 | 9 | 13 | 5 | 18 |
| 19 | Equatorial Guinea | 2 | 0 | 2 | 0 | 2 |
| 20 | Kenya | 3 | 3 | 6 | 15 | 21 |
| 21 | Lesotho | 1 | 2 | 3 | 1 | 4 |
| 22 | Liberia | 0 | 3 | 3 | 1 | 4 |
| 23 | Libya | 1 | 1 | 2 | 7 | 9 |
| 24 | Madagascar | 0 | 3 | 3 | 3 | 6 |
| 25 | Malawi | 0 | 3 | 3 | 2 | 5 |
| 26 | Mali | 0 | 4 | 4 | 6 | 10 |
| 27 | Mauritania | 0 | 2 | 2 | 6 | 8 |
| 28 | Mauritius | 1 | 6 | 7 | 7 | 14 |
| 29 | Morocco | 1 | 2 | 3 | 3 | 6 |
| 30 | Mozambique | 1 | 6 | 7 | 3 | 10 |
| 31 | Namibia | 0 | 2 | 2 | 1 | 3 |
| 32 | Niger | 0 | 4 | 4 | 2 | 6 |
| 33 | Nigeria | 1 | 1 | 2 | 2 | 4 |
| 34 | Rwanda | 0 | 4 | 4 | 2 | 6 |
| 35 | South Africa | 0 | 2 | 2 | 8 | 10 |
| 36 | Senegal | 1 | 5 | 6 | 7 | 13 |
| 37 | Seychelles | 0 | 2 | 2 | 3 | 5 |
| 38 | sierra Leone | 2 | 3 | 5 | 5 | 10 |
| 39 | South Sudan | 0 | 2 | 2 | 2 | 4 |
| 40 | Sudan | 0 | 1 | 1 | 7 | 8 |
| 41 | Swaziland | 0 | 2 | 2 | 1 | 3 |
| 42 | Tanzania | 6 | 14 | 20 | 9 | 29 |
| 43 | Tchad | 1 | 2 | 3 | 2 | 5 |
| 44 | Togo | 0 | 3 | 3 | 3 | 6 |
| 45 | Tunisia | 2 | 0 | 2 | 5 | 7 |
| 46 | Uganda | 3 | 8 | 11 | 3 | 14 |
| 47 | Zambia | 3 | 2 | 5 | 5 | 10 |
| 48 | Zimbabwe | 1 | 3 | 4 | 6 | 12 |
| **Total** | | **57** | **157** | **214** | **215** | **429** |

## References


Agoraki, M.-E.K., Delis, M.D., Pasiouras, F., 2011. Regulations, competition and bank risk-taking in transition countries. J. Financ. Stab. 7 (1), 38–48. https://doi.org/10.1016/j.jfs.2009.08.002.

Akande, J.O., Kwenda, F., Ehalaiye, D., 2018. Competition and commercial banks risk-taking: evidence from sub-Saharan Africa region. Appl. Econ. 50 (44), 4774–4787.

Allen, F., Gale, D., 2004. Competition and financial stability. J. Money Credit Bank. 453–480.

Anginer, D., Demirguc-Kunt, A., Zhu, M., 2014. How does competition affect bank systemic risk? J. Financ. Intermed. 23 (1), 1–26.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58 (2), 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econ. 68 (1), 29–51.

Arping, S., 2019. Competition and risk taking in banking: the charter value hypothesis revisited. J. Bank. Financ. 107, 105609.

Ashraf, B.N., 2017. Political institutions and bank risk-taking behavior. J. Financ. Stab. 29, 13–35. https://doi.org/10.1016/j.jfs.2017.01.004.

Assaf, A.G., Berger, A.N., Roman, R.A., Tsionas, M.G., 2019. Does efficiency help banks survive and thrive during financial crises? J. Bank. Financ. 106, 445–470.

Beck, T., 2015. Cross-border banking and financial deepening: the African experience. J. Afr. Econ. 24 (suppl_1), i32–i45.

Beck, T., De Jonghe, O., Schepens, G., 2013. Bank competition and stability: cross-country heterogeneity. J. Financ. Intermed. 22 (2), 218–244. https://doi.org/10.1016/j.jfi.2012.07.001.

Beck, T., Fuchs, M., Singer, D., Witte, M., 2014. Making Cross-Border Banking Work for Africa. Deutsche Gesellschaft für Internationale Zusammenarbeit …, Eschborn, Germany.

Berger, A.N., 1995. Problem Loans and Cost Efficiency in Commercial Banks, Vol. 95. Office of the Comptroller of the currency.

Berger, A.N., DeYoung, R., 1997. Problem loans and cost efficiency in commercial banks. J. Bank. Financ. 21 (6), 849–870.

Berger, A.N., Mester, L.J., 1997. Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions? Board of Governors of the Federal Reserve System Working Paper(1997–10).

Berger, A.N., DeYoung, R., Genay, H., Udell, G.F., 2000. Globalization of financial institutions: evidence from cross-border banking performance. Brookings-Wharton Papers on Finan. Serv. 2000 (1), 23–120.

Berger, A.N., Klapper, L.F., Turk-Ariss, R., 2009. Bank competition and financial stability. J. Financ. Serv. Res. 35 (2), 99–118.

Bikker, J.A., Haaf, K., 2002. Competition, concentration and their relationship: an empirical analysis of the banking industry. J. Bank. Financ. 26 (11), 2191–2214.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econ. 87 (1), 115–143.

Bordeleau, É., Graham, C., 2010. The Impact of Liquidity on Bank Profitability. Retrieved from Bank of Canada.

Boubakri, N., El Ghoul, S., Guedhami, O., Hossain, M., 2020. Post-privatization state ownership and bank risk-taking: cross-country evidence. J. Corp. Finan. 64, 101625.

Boyd, J.H., De Nicolo, G., 2005. The theory of bank risk taking and competition revisited. J. Financ. 60 (3), 1329–1343.

Boyd, J.H., Prescott, E.C., 1986. Financial intermediary-coalitions. J. Econ. Theory 38 (2), 211–232.

Broecker, T., 1990. Credit-worthiness tests and interbank competition. Econometrica: J. Economet. Soc. 429–452.
Chang, X., Chen, Y., Dasgupta, S., 2019. Macroeconomic conditions, financial constraints, and firms' financing decisions. J. Bank. Financ. 101, 242–255. https://doi.org/10.1016/j.jbankfin.2018.10.016.
Chen, M., Wu, J., Jeon, B.N., Wang, R., 2017. Do foreign banks take more risk? Evidence from emerging economies. J. Bank. Financ. 82, 20–39.
Chen, S., Nazir, M.I., Hashmi, S.H., Shaikh, R., 2019. Bank competition, foreign bank entry, and risk-taking behavior: cross country evidence. J. Risk Financ. Manag. 12 (3), 106.
Cubillas, E., González, F., 2014. Financial liberalization and bank risk-taking: international evidence. J. Financ. Stab. 11, 32–48.
Cyree, K.B., Spurlin, W.P., 2012. The effects of big-bank presence on the profit efficiency of small banks in rural markets. J. Bank. Financ. 36 (9), 2593–2603. https://doi.org/10.1016/j.jbankfin.2012.05.015.
Dbouk, W., Fang, Y., Liu, L., Wang, H., 2020. Do social networks encourage risk-taking? Evidence from bank CEOs. J. Financ. Stab. 46, 100708 https://doi.org/10.1016/j.jfs.2019.100708.
Demirgüç-Kunt, A., Huizinga, H., 2010. Bank activity and funding strategies: the impact on risk and returns. J. Financ. Econ. 98 (3), 626–650.
Demsetz, H., 1973. Industry structure, market rivalry, and public policy. J. Law Econ. 16 (1), 1–9.
Demsetz, R.S., Saidenberg, M.R., Strahan, P.E., 1996. Banks with something to lose: the disciplinary role of franchise value. Econ. Policy Rev. 2 (2).
Dinger, V., te Kaat, D.M., 2020. Cross-border capital flows and bank risk-taking. J. Bank. Financ. 117, 105842 https://doi.org/10.1016/j.jbankfin.2020.105842.
Fenn, P., Vencappa, D., Diacon, S., Klumpes, P., O'Brien, C., 2008. Market structure and the efficiency of European insurance companies: a stochastic frontier analysis. J. Bank. Financ. 32 (1), 86–100.
Fiordelisi, F., Marques-Ibanez, D., Molyneux, P., 2011. Efficiency and risk in European banking. J. Bank. Financ. 35 (5), 1315–1326. https://doi.org/10.1016/j.jbankfin.2010.10.005.
Foos, D., Norden, L., Weber, M., 2010. Loan growth and riskiness of banks. J. Bank. Financ. 34 (12), 2929–2940. https://doi.org/10.1016/j.jbankfin.2010.06.007.
Fu, X.M., Lin, Y.R., Molyneux, P., 2014. Bank competition and financial stability in Asia Pacific. J. Bank. Financ. 38, 64–77.
Gaganis, C., Pasiouras, F., 2013. Financial supervision regimes and bank efficiency: international evidence. J. Bank. Financ. 37 (12), 5463–5475.
Godspower-Akpomiemie, E., Ojah, K., 2021. Market discipline, regulation and banking effectiveness: do measures matter? J. Bank. Financ. 133, 106249 https://doi.org/10.1016/j.jbankfin.2021.106249.
Goetz, M.R., 2018. Competition and bank stability. J. Financ. Intermed. 35, 57–69.
Goetz, M.R., Laeven, L., Levine, R., 2016. Does the geographic expansion of banks reduce risk? J. Financ. Econ. 120 (2), 346–362. https://doi.org/10.1016/j.jfineco.2016.01.020.
Gormley, T.A., 2010. The impact of foreign bank entry in emerging markets: evidence from India. J. Financ. Intermed. 19 (1), 26–51. https://doi.org/10.1016/j.jfi.2009.01.003.
Hellmann, T.F., Murdock, K.C., Stiglitz, J.E., 2000. Liberalization, moral hazard in banking, and prudential regulation: are capital requirements enough? Am. Econ. Rev. 90 (1), 147–165.
Ho, T.H., Le, T.D., Nguyen, D.T., 2021. Abnormal loan growth and bank risk-taking in Vietnam: a quantile regression approach. Cogent Bus. Manag. 8 (1), 1908004.
Hughes, J.P., Mester, L.J., 1998. Bank capitalization and cost: evidence of scale economies in risk management and signaling. Rev. Econ. Stat. 80 (2), 314–325.
Jeon, B.N., Olivero, M.P., Wu, J., 2011. Do foreign banks increase competition? Evidence from emerging Asian and Latin American banking markets. J. Bank. Financ. 35 (4), 856–875. https://doi.org/10.1016/j.jbankfin.2010.10.012.
Jiménez, G., Lopez, J.A., Saurina, J., 2013. How does competition affect bank risk-taking? J. Financ. Stab. 9 (2), 185–195.
Kumbhakar, S.C., Lovell, C.K., 2003. Stochastic Frontier Analysis. Cambridge university press.
Léon, F., 2016. Does the expansion of regional cross-border banks affect competition in Africa? Indirect evidence. Res. Int. Bus. Financ. 37, 66–77.
Lepetit, L., Strobel, F., 2015. Bank insolvency risk and Z-score measures: a refinement. Financ. Res. Lett. 13, 214–224. https://doi.org/10.1016/j.frl.2015.01.001.
Louhichi, A., Louati, S., Boujelbene, Y., 2020. The regulations–risk taking nexus under competitive pressure: what about the Islamic banking system? Res. Int. Bus. Financ. 51, 101074 https://doi.org/10.1016/j.ribaf.2019.101074.
Lozano-Vivas, A., Weill, L., 2012. How does cross-border activity affect EU banking markets? Eur. Financ. Manag. 18 (2), 303–320.
Marcus, A.J., 1984. Deregulation and bank financial policy. J. Bank. Financ. 8 (4), 557–565.
Mare, D.S., Moreira, F., Rossi, R., 2017. Nonstationary Z-score measures. Eur. J. Oper. Res. 260 (1), 348–358. https://doi.org/10.1016/j.ejor.2016.12.001.
Martinez-Miera, D., Repullo, R., 2010. Does competition reduce the risk of bank failure? Rev. Financ. Stud. 23 (10), 3638–3664.
Matousek, R., Rughoo, A., Sarantis, N., George Assaf, A., 2015. Bank performance and convergence during the financial crisis: evidence from the 'old' European Union and Eurozone. J. Bank. Financ. 52, 208–216. https://doi.org/10.1016/j.jbankfin.2014.08.012.
Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. J. Financ. 29 (2), 449–470.
Moyo, B., 2018. An analysis of competition, efficiency and soundness in the south African banking sector. S. Afr. J. Econ. Manag. Sci. 21 (1), 1–14.
Mpofu, T.R., Nikolaidou, E., 2018. Determinants of credit risk in the banking system in sub-Saharan Africa. Rev. Develop. Fin. 8 (2), 141–153.
Nakamura, L.I., 1993. Loan Screening Within and Outside of Customer Relationships. Retrieved from.
Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica: J. Economet. Soc. 1417–1426.
Oduor, J., Ngoka, K., Odongo, M., 2017. Capital requirement, bank competition and stability in Africa. Rev. develop. Fin. 7 (1), 45–51.
Panzar, J.C., Rosse, J.N., 1987. Testing for" monopoly" equilibrium. J. Ind. Econ. 443–456.
Pelletier, A., 2018. Performance of foreign banks in developing countries: evidence from sub-Saharan African banking markets. J. Bank. Financ. 88, 292–311. https://doi.org/10.1016/j.jbankfin.2017.11.014.
Phan, H.T., Anwar, S., Alexander, W.R.J., Phan, H.T.M., 2019. Competition, efficiency and stability: an empirical study of east Asian commercial banks. The North Am. J. Econom. Fin. 50, 100990 https://doi.org/10.1016/j.najef.2019.100990.
Porta, R.L., Lopez-de-Silanes, F., Shleifer, A., Vishny, R.W., 1998. Law and finance. J. Polit. Econ. 106 (6), 1113–1155.
Restrepo-Tobón, D., Kumbhakar, S.C., 2014. Enjoying the quiet life under deregulation? Not quite. J. Appl. Econ. 29 (2), 333–343.
Roodman, D., 2009. A note on the theme of too many instruments. Oxf. Bull. Econ. Stat. 71 (1), 135–158.
Salas, V., Saurina, J., 2002. Credit risk in two institutional regimes: Spanish commercial and savings banks. J. Financ. Serv. Res. 22 (3), 203–224.
Schaeck, K., Čihák, M., 2010. Competition, Efficiency, and Soundness in Banking: An Industrial Organization Perspective. *European banking center discussion Paper* (2010-20S).
Seven, U., Coskun, Y., 2016. Does financial development reduce income inequality and poverty? Evidence from emerging countries. Emerg. Mark. Rev. 26, 34–63. https://doi.org/10.1016/j.ememar.2016.02.002.
Shaban, M., James, G.A., 2018. The effects of ownership change on bank performance and risk exposure: evidence from Indonesia. J. Bank. Financ. 88, 483–497. https://doi.org/10.1016/j.jbankfin.2017.02.002.
Stiglitz, J.E., Weiss, A., 1981. Credit rationing in markets with imperfect information. Am. Econ. Rev. 71 (3), 393–410.
Tabak, B.M., Fazio, D.M., Cajueiro, D.O., 2012. The relationship between banking market competition and risk-taking: do size and capitalization matter? J. Bank. Financ. 36 (12), 3366–3381. https://doi.org/10.1016/j.jbankfin.2012.07.022.
Uddin, A., Chowdhury, M.A.F., Sajib, S.D., Masih, M., 2020. Revisiting the impact of institutional quality on post-GFC bank risk-taking: evidence from emerging countries. Emerg. Mark. Rev. 42, 100659 https://doi.org/10.1016/j.ememar.2019.100659.
Vasicek, O., 2002. The distribution of loan portfolio value. Risk 15 (12), 160–162.
Williamson, S.D., 1986. Costly monitoring, financial intermediation, and equilibrium credit rationing. J. Monet. Econ. 18 (2), 159–179. https://doi.org/10.1016/0304-3932(86)90074-7.

Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. J. Econ. 126 (1), 25–51.
Wu, J., Chen, M., Jeon, B.N., Wang, R., 2017. Does foreign bank penetration affect the risk of domestic banks? Evidence from emerging economies. J. Financ. Stab. 31, 45–61. https://doi.org/10.1016/j.jfs.2017.06.004.
Wu, J., Guo, M., Chen, M., Jeon, B.N., 2019. Market power and risk-taking of banks: some semiparametric evidence from emerging economies. Emerg. Mark. Rev. 41, 100630 https://doi.org/10.1016/j.ememar.2019.100630.
Wu, J., Chen, L., Chen, M., Jeon, B.N., 2020. Diversification, efficiency and risk of banks: evidence from emerging economies. Emerg. Mark. Rev. 45, 100720 https://doi.org/10.1016/j.ememar.2020.100720.
Zheng, C., Cheung, A., Cronje, T., 2019. The moderating role of capital on the relationship between bank liquidity creation and failure risk. J. Bank. Financ. 108, 105651 https://doi.org/10.1016/j.jbankfin.2019.105651.
Zhu, W., Yang, J., 2016. State ownership, cross-border acquisition, and risk-taking: evidence from China's banking industry. J. Bank. Financ. 71, 133–153.