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# The Role of Banking Concentration on Financial Stability

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**Abstract**

Globally, financial instability is a major source of concern among policy makers and bank regulators, particularly after the 2007-09 global financial crisis. Motivated by inconsistent theoretical evaluations on the impact of bank concentration on the likelihood of a systemic banking crisis, this paper investigates the role of bank concentration on financial stability in Kenya with competition as an intervening variable. The novelity of this study lies on the use of structural equation modeling (SEM) in the analysis of direct and indirect effects of bank concentration on financial stability. Results show that higher concentration induces banks to increase cost of service provision which may aggravate credit risks and expose banks to systemic risks. Further, competition plays a significant role in ensuring financial system stability which supports the 'competition-stabiliy' hypothesis. Uncompetitive banking industry may therefore provide incentive for banks to take excessive risks, which renders them vulnerable to systematic risks. We also establish that tight regulations enhances concentration and financial stability but hinders competition. These new insights give bank regulators and policy makers an incentive to formulate and implement the right policies to improve financial stability.

**Keywords:** financial stability, structural equation model, bank concentration, banking fragility, bank competition

## 1. Introduction

Banking concentration has ignited interest among scholars and policy makers, since it may have exacerbated the 2007-2009 global financial crisis (Calice & Leone, 2018). Proponents of "concentration-stability" hypothesis argue that few banks are easy to control and can be able to diversify efficiently thereby earning high profits. This acts as a buffer during financial crises (Beck, Demirgüç-Kunt, & Levine, 2003). Moreover, higher bank concentration leads to greater financial inclusion, which enhances financial stability (Owen & Pereira, 2018). On the contrary, "concentration-fragility" hypothesis suggests that fewer banks are large and complex. This makes them difficult to monitor and hence they exploit customers by charging high interest, which induces customers to invest in risky ventures (Boyd & De Nicolo, 2005). Bank concentration also encourages moral hazard behavior centered on the notion of 'too big to fail' policies (Feldman, 2015).

Motivated by these concerns, this study seeks to investigate the effect of bank concentration on financial stability in Kenya. The banking sector has experienced dramatic reforms in terms of structure and regulation since the year 2000. These reforms include the establishment of a financial sector regulatory framework, digital finance, the formation of credit registries, and a national payment system among other reforms. In the past fifteen years, the banking sector has witnessed seven mergers. While the five large banks control more than 50% of the market share, the debate on how bank concentration affects stability of the financial system is still not clear. Previous studies on the Kenyan banking sector context have explored the dynamics of concentration and competition among commercial banks focusing on profitability, changes in technology and consolidation, ignoring the aspect of financial stability (see Mdoe, Omolo, & Wawire, 2019; Sahile, Tarus, & Cheriyot, 2015). This is our point of departure. Consistent with this research gap, two critical questions remain unresolved: What is the effect of bank concentration on financial stability in Kenya? Does the banking system support the 'concentration-stability' or 'the concentration-fragility theory'?

This study supports the existing literature in several ways. First, it is timely in view of the growing emphasis on financial stability by policy makers across the globe. Second, to the best of our knowledge, this is the first study to examine how banking concentration affects financial stability in Kenya. Third, this study pioneers the use of structural equation modeling (SEM) technique in analyzing both direct and indirect effects of bank concentration on financial stability. SEM enables us to tackle the problem of approximating measurement errors. Finally, understanding the channel through which banking concentration impacts financial stability is vital for the development of operative structural policies particularly entry/exit rules, restrictions of activities and consolidation policies. This paper is organized as follows; the next section presents a brief literature review. Section three covers theoretical framework. Methodology and data are covered in section four. Estimation and discussion of results are presented in section five while section six concludes the study.

## 2. Literature Review

This section reviews recent empirical evidence on banking concentration and financial stability. We focus on two strands in the literature that are closest to our analysis. These are “concentration-stability” and “concentration-fragility” hypotheses. The “concentration-stability” hypothesis suggests that there is a significant association between bank concentration and financial stability through profitability channel (Berger, Klapper, & Turk-Aris, 2009; Vives, 2010; Berger & Bouwman, 2013), diversification channel (Frey & Hledik, 2018; Evrensel, 2008) and efficiency channel (Cifter, 2015). Using structural matrix approach on Brazilian data and Hirschman-Herfindahl index to proxy bank concentration Chang, Lima, Guerra, and Tabak (2008) concluded that a concentrated banking system is less prone to a financial crisis. Further, Vives (2010) found that few banks in a concentrated market earn greater profits that act as a buffer during financial crises. In a related development, Evrensel (2008) used survival time analysis to show that bank concentration improves the survival time of banks during a crisis. It is therefore apparent that bank concentration significantly reduces banks’ fragility during a crisis.

On the contrary, “concentration-fragility” hypothesis contends that too much concentration may lead to higher lending rates that would exacerbate default risks (IJtsma, Spierdijk, & Shaffer, 2017; Mirzaei, Moore, & Liu, 2013; Uhde & Heimeshoff, 2009). In concentrated markets, as bank institutions get bigger and more diversified, the risks of their portfolios may increase, (Boyd, De Nicolo, & Jalal, 2006), internal inefficiencies and increased operational risk may as well increase (Laeven & Levine, 2007) with implications on monitoring due to moral hazard and the notion of "too big to fail" policies (Feldman, 2015). Despite banks holding high capital in a concentrated market, the number of assets they own is not large enough to mitigate the effect of non-payment risks linked to higher risk-taking business organizations (Soedarmono, Machrouh, & Tarazi, 2013). Larger banks also tend to raise borrowing rates that lead to adverse selection, which in turn attracts risky bank customers (Berger et al., 2009). Further, accumulation of risky assets increases the fragility of the banking system (Altunbas, Manganelli, & Marques-Ibanez, 2011). These results are consistent with the “concentration-fragility” hypothesis.

The seminal work on “competition-stability” hypothesis is due to Mishkin (1999). This hypothesis posits that increased competition reduces the possibility that a country will be exposed to a financial crisis. Using data of 978 banks from 55 developing economies, Amidu and Wolfe (2013) examine the outcome of diversification on competition and stability. The study used three-stage least square regression and H-statistics to estimate competition. The study concludes that competition increases diversification in both non-interest revenue and interest revenue of banks. Shijaku (2017) utilized Generalized Methods of Moments (GMM) approach to investigate the consequences of competition on bank stability in Albania’s banking system employing data of sixteen banks for the period 2008-2015. The study outcomes reveal that competition plays an important role in ensuring bank stability. This finding supports (Sanya & Wolfe, 2011).

Upcoming literature on competition and financial stability seems to be consistent with competition-fragility hypothesis (Agoraki, Delis, & Pasiouras, 2011; Beck, Demirgüc-Kunt, & Merrouche, 2013; Cifter, 2015; Kick & Prieto, 2015; Leroy & Lucotte, 2016). When there is perfect competition in the banking sector each bank mobilizes few customers as reflected by the little sum of deposit in their till. Therefore, no bank has an effect in determining interest to be charged in the market. However, banks will be induced to expand business activities and take more risks as long as they earn positive returns. This increased competition may lead to investments in risky ventures that would trigger systemic risks (Agoraki et al., 2011). Competition reduces the ability of banks to control the prices of their products and at the same time acts as an inducement for banks to capitalize in riskier ventures (Berger et al., 2009).

Along the same vein, Agoraki et al. (2011) employ a static panel data instrumental variable regression on Eastern and Central European banks for the period 1998 to 2005. The study findings reveal that less bank concentration encourages competition, which in turn increases credit risk with a higher probability of default. Further, Leroy and Lucotte (2016) evaluate the trade-off between competition and financial system stability of 54 European banks using Stochastic Frontier Analysis (SFA) approach between 2004 and 2013. The study outcomes confirm competition-fragility hypothesis which is consistent with Cifter (2015). A competition that is induced by reduced regulation does not automatically improve financial stability (Kick & Prieto, 2015). Examining data of 415 banks in Central and Eastern European Countries (CEEC) for the period 1997-2012 and a fixed effect panel regression, Jimenez, Lopez, and Saurina (2013) establish that bank competition increases instability of the financial sector over time.

In a formative paper, Beck, Demirgüç-Kunt, and Levine (2007) investigate the impact of concentration on stability through diversification and the ease of monitoring indicators. The study findings disclose that only diversification plays a role in ensuring stability of the banking system. Bretschger, Kappel, and Werner (2012) controlled for both profitability and the cost of credit in their study of 160 countries for the period 1970-2009. Estimation results found a varying channel effect of concentration-stability and concentration-fragility in most developed and less developed countries. The net effect of these variables however remains ambiguous. Adusei and Elliott (2015) investigate whether bank size significantly explains the variations in bank stability in Ghana. The results reveal that size matters for the stability of a rural bank. TengTeng, Kun, and Adaibir (2019) examine how bank profitability influences financial stability. The study findings confirm that profitability is inversly related to systemic and idiosyncratic risks. Further, Atoi (2018) investigates the impact of non-performing loans (NPLs) on the stability of Nigerian banks. Regression results find that the stability of national banks is vulnerable to NPLs shocks in the long run. Using a sample of 49 banks operating in the MENA region, Ghenimi, Chaibi and Omri (2017) approve that credit and liquidity risks jointly do not have a contemporaneous relationship but the interaction of both risks contributes to bank instability.

Although existing literature does not explain the ambiguity of theoretical predictions, these previous findings suggest that bank concentration and competition can determine financial stability. The evidence is however mixed. One plausible explanation for the divergent findings is that the control variables through which concentration may impact financial stability are at work simultaneously, with different net effects and magnitude on financial stability. Moreover, empirical literature on how bank concentration and competition affects financial stability in certain regional contexts such as the Sub-Saharan African (SSA) region and more specifically in Kenya remain unexplored.

## 3. Methodology and Data

### *3.1 Empirical Model*

There is no consensus in the existing literature on how concentration affects financial stability. The appropriate model to explore this relationship is the structural equation model (Li, 2016). SEM is the most appropriate model to GMM and panel data regression because latent construct cannot be estimated directly and have measurement errors. Further, SEM reports the variance, covariance and multiple multilevel regression results that shows the interaction between our latent constructs (see Kline, 2005; Boomsma, 2000). In our SEM model, concentration is assumed to have a single direct effect and indirect effect on financial stability. The indirect effect is captured by competition and the path is concentration-competition-stability respectively. SEM encompasses two models that include the measurement and structural model. The measurement model is specified as:

$$Z = \Phi_z \Omega + \Lambda, \tag{1}$$

Where Z is a vector of exogenous variables that can be observed z; $\Omega$ represents a vector of exogenous latent indicator $\rho$. The matrix of factor loading $\Phi_z$ is represented by $\varphi_z$. When we link $z$ to $\rho$ then we have $\Lambda$ as a vector of measurement errors $\varepsilon$. Therefore, our exogenous variable is defined as;

$$\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} = \begin{bmatrix} \varphi_{z1} \\ \varphi_{z2} \\ \vdots \\ \varphi_{z_n} \end{bmatrix} \rho + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{2}$$

In our study, bank concentration is defined as $\rho$ and measured by observable variables $z_1, z_2, \ldots\ldots z_n$. The coefficients of bank concentration ($\rho$) are represented by $\varphi_{z1}, \varphi_{z2}, \ldots.., \varphi_{zn}$ while $\varepsilon_1, \varepsilon_2, \ldots.., \varepsilon_n$ denotes the error term. Likewise, we present the measurement model of the endogenous indicators as;

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \lambda_{1\gamma} & 0 & 0 \\ \lambda_2 & \lambda_3 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & \lambda_n \end{bmatrix} \begin{bmatrix} \gamma_1 \\ \gamma_2 \end{bmatrix} + \begin{bmatrix} \vartheta_1 \\ \vartheta_2 \\ \cdot \\ \cdot \\ \vartheta_n \end{bmatrix}, \tag{3}$$

Where $y_1, y_2, y_3 \ldots\ldots, y_n$ are variables that proxy the endogenous variables, which include competition $\gamma_1$and financial stability $\gamma_2$. However, it should be noted that not all measurement variables have been included to proxy our endogenous variables. For instance, we know that macroeconomic environment and the level of financial inclusion also affect bank competition and financial stability but are not used as measurement variables. An endogenous variable mutually represents a cause or effect of an outcome. In our case competition can be regarded as both the cause of financial stability and has an effect on bank concentration. Further, $\vartheta_1, \vartheta_2, \ldots\ldots, \vartheta_n$ represents the residual terms of the estimated model.

Our structural equation model, therefore, merges the measurement and the path model by considering residuals of measurement observable variables as follows;

$$N = AN + \Omega\Psi + \Upsilon, \tag{4}$$

Where N represents a matrix of path coefficients $\eta$, which explains the link between endogenous latent construct. Further, $\Omega$ is the path matrix of coefficient $\tau$ that explains the direct effects of exogenous measurement variables on endogenous measurement indicators. Finally, $\Upsilon$ is a vector of estimation residuals $\upsilon$. The SEM model is presented as follows:

$$\begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ \eta_{21} & 0 & 0 \\ 0 & \eta_{32} & \eta_{33} \end{bmatrix} \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \end{bmatrix} \rho + \begin{bmatrix} \upsilon_1 \\ \upsilon_2 \\ \upsilon_3 \end{bmatrix}, \tag{5}$$

*3.2 Definition of Variables*

Preceding studies have utilized different concentration ratios to measure the market share of banks. For this study we use Herfindahl-Hirschman Index (HH). It is the most widely used measure (Bikker & Haaf, 2002). It is estimated as the sum of squares of the market share of loans, assets, or deposits of each bank in the banking sector. The ratio is defined as:

$$HHI = \sum_{i=1}^{n} \left(\frac{x_i}{X}\right)^2 \qquad\qquad 1 \geq HHI \geq \frac{1}{n}, \tag{6}$$

Where $X$ is the joint assets of all commercial banks in a country, $x_i$ is the total asset of bank $i$ in a given period and there are $n$ banks in the country. HHI varies between 1 and $1/n$. A value of 1 signifies a monopoly market and the lowest value of $1/n$, implies all banks are equal in size. Bank concentration is high if the value exceeds 0.18 and medium if it ranges between 0.1 and 0.18. It is small when it is below 0.1. Therefore, Davies (1979) posits that the HHI is less responsive to alterations in the quantity of banks when the number of banks increases. We compute the HHI of the banks in Kenya and use it as one of the measures of bank concentration.

We also use banks' concentration ratio ($CR_n$) which measures the sum of assets held by $n$ largest banks divided by the total assets held by the banking sector computed as follows;

$$CR_n = \sum_{i=1}^{n} \frac{x_i}{X}, \tag{7}$$

Policy makers often utilize this ratio when measuring the market composition and formulating bank regulations (Berger, Demirgüç-Kunt, Levine, & Haubrich, 2004). Regulators may utilize concentration ratios by focusing on how size; number of banks and distribution affect competition. Our study employs the share of assets held by the five leading banks in Kenya.

Studies conducted on competition and stability differentiate between structural and non-structural measures. The most commonly used structural measure is the market share while non-structural competitive measures are the Lerner Index (1934); H-statistics (1987) and the modified Boone Indicator (2008). Based on existing literature (see Park, 2013; Amidu & Wolfe, 2013) and reliability of the measures, our study adopts the non-structural estimates, specifically the Lerner Index, H-Statistics and the Boone Indicator to proxy competition.

Lerner index (LI) is calculated as the variation between price and marginal cost as a fraction of price. It is the converse proxy for competition and can be estimated as;

$$LI_{it} = \frac{p_{it} - mc_{it}}{p_{it}}, \tag{8}$$

Where $p_{it}$ proxies price of bank $i's$ output at time $t$ and $mc_{it}$ is the marginal cost of bank $i$ at time $t$. The LI measured for each bank represents its pricing influence in the market, $p_{it}$ is estimated by dividing the total income with total assets (Beck, Demirgüç-Kunt, & Merrouche 2013). LI ranges from 0 to 1. The value of 1 represents pure monopoly while zero corresponds to a perfectly competitive market. LI is preferred to other measures because it can be calculated at the firm level over a longer period (Leroy & Lucotte, 2006).

H-statistics (HS) introduced by Panzar and Rosse in 1987 is the summation of elasticities of the reduced form incomes with respect to factor prices. This measure varies between $-\infty < H \leq 1$. When the H-statistics value is less than zero, the market is a pure monopoly ($-\infty < H \leq 0$). Further, when the H-statistics range between zero to one then it is a monopolistic or an oligopolistic market rivalry ($0 < H < 1$). When the H-statistics value is equivalent to one ($H = 1$), then we have a perfectly competitive market. H-statistics is computed as follows:

$$H = \sum_{k-1}^{m} \left( {\partial R_i^*}/{\partial w_{k_i}} \right) \left( {w_{k_i}}/{R_i^*} \right), \tag{9}$$

Where * represent variables that are in equilibrium. Market dominance is estimated by the degree to which an alteration in factor input cost ($\partial w_{k_i}$) is replicated in the equilibrium income ($\partial R_i^*$) received by bank $i$.

Boone indicator (BO) estimates the differences in efficiency of firms in a given sector. Banks that are more efficient significantly improve their performance compared to less efficient banks. The Boone indicator links performance with different levels of efficiency (Boone, 2008). The revenue elasticity index known as the Boone index is estimated as follows;

$$\pi_{it} = \delta + \theta \ln(MC_{it}), \tag{10}$$

Where $i$ represents an individual bank, while $t$ stands for a sample year. $\pi_{it}$ symbolizes performance in terms of profit and $MC_{it}$ is the marginal cost of an individual bank at a given year. Efficient firms with less marginal cost have a higher market command, reduced prices, higher revenues and higher price-cost margins (Aghion, Bloom, Blundell, Griffith, & Howitt, 2005). Some studies may replace market performance with market share when measuring the efficiency of banks (Tabak, Fazio, & Cajueiro, 2011). Profit in the banking sector is estimated by deducting bank-operating expenses from bank operating income. Further, due to difficulties in measuring the marginal cost, we use the average cost. $\theta$ is a proxy for the Boone indicator. It is always negative due to decreasing function of revenue as a result of the bank's inefficiency. Higher values of $\theta$ in absolute terms signify tougher competition.

Further, we include bank regulation indicators as a control variable in our estimation. We use capital adequacy (CA) and asset quality (AQ) to proxy micro-prudential regulation while minimum capital requirement (MC) and debt to income ratio (DI) represent macro- prudential ratio. Bank regulations also affect the degree of bank concentration and competition in the market (Demirguc-Kunt & Datragiache, 2002).

Financial stability comprises financial resilience and financial volatility. This study used proxies that capture system-wide risks through resilience and volatility of the financial sector. Banks' Z-score (ZS) and the ratio of credit provisioning to bank deposit (CB) are used to measure financial system resilience (Beck et al., 2013). Z-score is the inverse of the probability of insolvency and it shows the number of standard deviations the ROA must decrease below its probable cost before capital is exhausted and the bank becomes insolvent (De Nicolo, 2000). Credit provisioning ratio estimates the potential loss that banks may experience due to credit risks. They are anticipated losses from bad debt or other lendings that have a high probability of being defaulted or unrecoverable. As this ratio increases, banks become vulnerable to potential risks in the financial system. The volatility of the financial system is represented by the standard deviation of deposit growth rate (SL) and standard deviation of lending growth rate (SB). A wider variation of data signifies a higher deviation. Standard deviation is derived from the square root of variance. We apply the same procedure in deriving the standard deviation of banks' deposit rates. Loan loss reserve to total loan loss ratio (LL) is used to show the reserves that banks make in percentage to cover anticipated losses it may incur due to credit default (Cihak & Melecky, 2016).

### *3.3 Data Sources*

This study is based on aggregate variables estimates of all the 40 banking firms in Kenya. The analysis uses time-series data for the period 1990-2017. Yearly data of our variables of interest were obtained from World Bank's Global Financial Development Database (GFDD), Thomson Reuter's database and the Central Bank of Kenya (CBK). Our selection of data period was guided by some important changes in bank concentration, competition and financial stability in Kenya. For example, since 2004 medium-sized banks improved their efficiency hence edging closer to large-sized banks over time.

## 4. Empirical Findings

Table 1 presents the summary statistics. The maximum mean value of our data is that of the Z-score at 12.26 and the minimum value is that of Boone indicator at 0.09. Most variables are lowly dispersed from their means as reflected by low standard deviations. The highest and lowest values in the data are depicted by the maximum and lowest values. All variables have a significantly peaked distribution as represented by positive kurtosis values. The highest peaked distributions are shown by Panzar Rosse H-statistics and loan loss reserve to total loan loss ratio. All variables are normally distributed at a five percent significant level. The adjusted chi-square probability numbers outside the brackets factor in small sample distribution values that delay converging under the JB statistics. Therefore, the data is normally distributed.

Table 1. Descriptive statistics

| Variables | Obs | Mean | Std. Dev. | Min | Max | Skewness | kurtosis | Pr(JB-stat) |
|---|---|---|---|---|---|---|---|---|
| Herfindahl-Hirschman Index (HH) | 28 | 0.10 | 0.05 | 0.03 | 0.19 | -0.08 | 2.38 | 2.89[0.24] |
| 5 Bank Concentration (CR) | 28 | 0.70 | 0.30 | 0.49 | 0.70 | -0.40 | 2.40 | 4.12[0.13] |
| Boone Indicator (BO) | 28 | 0.09 | 0.06 | 0.01 | 0.26 | 0.22 | 2.38 | 0.19[0.91] |
| Panzar-Rosse H-Statistics (HS) | 28 | 0.52 | 0.11 | 0.34 | 0.72 | -0.95 | 3.77 | 1.09[0.65] |
| Lerner Index (LI) | 28 | 0.41 | 0.07 | 0.28 | 0.54 | -0.55 | 2.37 | 0.72[0.70] |
| Capital adequacy (CA) | 28 | 0.38 | 0.26 | 0.11 | 0.88 | -0.65 | 2.89 | 0.30[0.18] |
| Asset quality (AQ) | 28 | 0.44 | 0.21 | 0.15 | 0.80 | -0.32 | 2.15 | 4.95[0.08] |
| Minimum capital requirement (MC) | 28 | 0.47 | 0.21 | 0.10 | 0.89 | -0.43 | 2.50 | 4.79[0.09] |
| Debt to operating income ratio of banks (DI) | 28 | 0.49 | 0.25 | 0.11 | 0.87 | -0.75 | 3.10 | 0.80[0.60] |
| Z-score (ZS) | 28 | 12.26 | 2.35 | 8.50 | 16.3 | -0.06 | 2.10 | 0.30[0.18] |
| Ratio of Credit Provision to Bank Deposit (CB) | 28 | 0.33 | 0.19 | 0.02 | 0.63 | -0.42 | 1.68 | 3.38[0.12] |
| Standard Dev of Banks' Lending Rate (SL) | 28 | 0.47 | 0.20 | 0.11 | 0.93 | 0.75 | 2.28 | 2.39[0.30] |
| Standard Dev of Banks Deposit Rate (SB) | 28 | 0.31 | 0.16 | 0.09 | 0.67 | 1.46 | 1.63 | 2.88[0.23] |
| Loan loss reserve to total loans ratio (LL) | 28 | 0.51 | 0.17 | 0.10 | 0.80 | -0.99 | 3.22 | 0.93[0.63] |

Table 2 presents a correlation matrix. It shows an inverse relationship between bank concentration and financial stability in Kenya as depicted by variables that represent concentration (HH, CR) and variables that represent financial stability (ZS, CB, SB, SL, LL). This supports the 'concentration-fragility' hypothesis.

Table 2. Correlation matrix

| | CR | HH | BO | HS | LI | CA | AQ | MC | DI | ZS | CB | SB | SL | LL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CR | 1.00 | | | | | | | | | | | | | |
| HH | 0.30 | 1.00 | | | | | | | | | | | | |
| BO | -0.42 | -0.21 | 1.00 | | | | | | | | | | | |
| HS | 0.33 | 0.03 | -0.13 | 1.00 | | | | | | | | | | |
| LI | 0.40 | 0.41 | -0.15 | -0.31 | 1.00 | | | | | | | | | |
| CA | -0.35 | -0.32 | 0.27 | 0.29 | 0.37 | 1.00 | | | | | | | | |
| AQ | -0.48 | -0.47 | 0.12 | 0.40 | 0.45 | 0.38 | 1.00 | | | | | | | |
| MC | -0.12 | -0.32 | 0.28 | -0.31 | -0.23 | 0.34 | 0.04 | 1.00 | | | | | | |
| DI | -0.25 | -0.30 | 0.38 | -0.26 | -0.34 | 0.23 | 0.10 | 0.35 | 1.00 | | | | | |
| ZS | -0.71 | -0.47 | 0.33 | -0.08 | -0.02 | 0.29 | 0.28 | 0.32 | 0.08 | 1.00 | | | | |
| CB | -0.56 | -0.48 | 0.10 | -0.18 | -0.40 | 0.39 | 0.16 | 0.27 | 0.19 | 0.60 | 1.00 | | | |
| SB | -0.11 | -0.41 | 0.05 | -0.18 | -0.02 | 0.24 | 0.13 | 0.26 | 0.26 | 0.29 | 0.33 | 1.00 | | |
| SL | -0.44 | -0.37 | 0.42 | -0.10 | - 0.25 | 0.35 | 0.24 | 0.45 | 0.12 | 0.33 | 0.45 | 0.66 | 1.00 | |
| LL | -0.02 | -0.03 | 0.21 | -0.40 | - 0.33 | 0.42 | 0.19 | 0.23 | 0.16 | -0.13 | 0.08 | -0.51 | -0.09 | 1.00 |

To ensure that we get reliable results that would explain our four latent variables, we performed a rotation on the four factors to establish the correlation between the factors and the original measurement variables. We further used an orthogonal matrix rotation known as varimax rotation to ascertain the composition of the scale factor. Two variables that had factor loadings of less than 0.5 were dropped. They included minimum capital requirement (MC) and Loan loss reserve to total loans ratio (LL). Table 3 shows how the remaining variables loaded on the three factors. Factor 1 includes variables that represent bank concentration namely: 5 banks concentration ratio (CR) and Herfindahl-Hirschman Index (HH). Factor 2 includes variables that proxy banking stability namely: bank Z-score (ZS), Ratio of Credit Provision to Bank Deposit (CB), standard deviation of bank's deposit rate (SB) and standard deviation of bank's lending rate (SL). The third and fourth factors constituted measurement indicators that proxied banks' competition and regulations. These are Boone Indicator (BO), Panzar-Rosse H-Statistics (HS) and the Lerner Index (LI), capital adequacy (CA), asset quality (AQ) and debt to operating income ratio of banks (DI). The uniqueness column represents the error term of the variables that are not explained by the existing three factors. The Z-score (ZS) and standard deviation of bank's lending rate (SL) have the highest unique value at 0.19. This implies that 19% of the residual of ZS and SL are not explained by the second factor.

Table 3. Factor rotation matrix using varimax

| Variable | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Uniqueness |
|---|---|---|---|---|---|
| CR | -0.84 | | | | 0.18 |
| HH | -0.77 | | | | 0.17 |
| BO | | | 0.91 | | 0.15 |
| HS | | | -0.60 | | 0.12 |
| LI | | | 0.88 | | 0.18 |
| CA | | | | 0.78 | 0.07 |
| AQ | | | | 0.82 | 0.13 |
| DI | | | | 0.72 | 0.05 |
| ZS | | 0.88 | | | 0.19 |
| CB | | 0.92 | | | 0.09 |
| SB | | 0.89 | | | 0.19 |
| SL | | 0.81 | | | 0.10 |

We further constructed a scree plot to determine the most effective factors that would significantly affect our estimation model. Figure 1 shows the scree plot of the Eigen values.

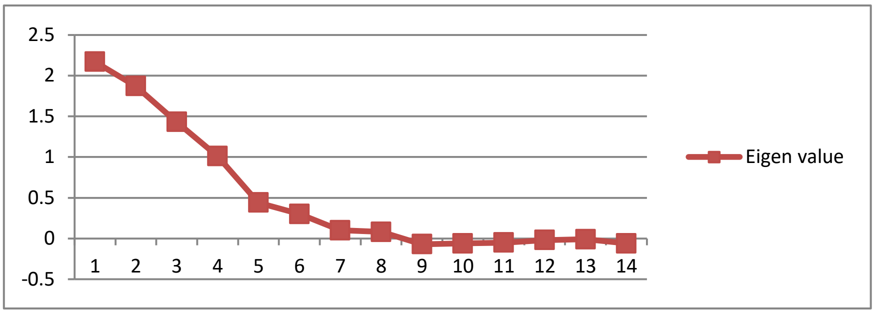


Figure 1. Scree plot of eigen values

### *4.1 Reliability and Adequacy Test*

Table 4 shows the outcome of Cronbach's Alpha (CA) reliability test. The coefficient of alpha ($\alpha$) varies between 0 and 1. Scores higher than 0.7 meet the expected threshold. However, some studies (see e.g. Tavakol & Dennick, 2011) propose a score higher than 0.9. All our variables of interest are statistically significant since the calculated correlation between the scale validity coefficient and the square root of alpha ($\sqrt{0.79}$) is slightly close to 0.90 as reflected by CA of 0.79 and average interim correlation of 0.24.

Table 4. Cronbach's Alpha reliability test

| Item | Obs | Sign | Item-test correlation | Item-rest correlation | Average Interim correlation | Alpha |
|---|---|---|---|---|---|---|
| CR | 28 | - | 0.82 | 0.78 | 0.26 | 0.77 |
| HH | 28 | - | 0.78 | 0.74 | 0.28 | 0.80 |
| BO | 28 | + | 0.77 | 0.72 | 0.25 | 0.76 |
| HS | 28 | - | 0.61 | 0.58 | 0.25 | 0.76 |
| LI | 28 | - | 0.80 | 0.76 | 0.23 | 0.89 |
| CA | 28 | + | 0.78 | 0.74 | 0.26 | 0.81 |
| AQ | 28 | + | 0.85 | 0.83 | 0.27 | 0.76 |
| DI | 28 | + | 0.74 | 0.69 | 0.24 | 0.74 |
| ZS | 28 | + | 0.63 | 0.60 | 0.23 | 0.72 |
| CB | 28 | + | 0.81 | 0.77 | 0.27 | 0.86 |
| SB | 28 | + | 0.61 | 0.58 | 0.21 | 0.70 |
| SL | 28 | + | 0.77 | 0.72 | 0.18 | 0.89 |
| TEST SCALE | | | | | 0.24 | 0.79 |

We further used the Kaiser-Meyer-Olkin (KMO) test to calculate the sampling competence for each variable and the model. KMO values vary between 0 and 1. Individual KMO outcome for each indicator and the model is presented in Table 5. Higher KMO values imply that our model is consistent for factor analysis. Kline (2005) recommends KMO values above 0.7. The outcome of our data shows a KMO of 0.86 which is higher than 0.7. This justifies the use of factor analysis.

Table 5. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy

| Variable | KMO |
|---|---|
| CR | 0.86 |
| HH | 0.90 |
| BO | 0.88 |
| HS | 0.89 |
| LI | 0.84 |
| CA | 0.91 |
| AQ | 0.87 |
| DI | 0.82 |
| ZS | 0.85 |
| CB | 0.92 |
| SB | 0.80 |
| SL | 0.77 |
| Overall | 0.86 |

### *4.2 Confirmatory Factor Analysis (CFA)*

We set a measurement scale of unobserved latent construct variables variance to 1 (Brown, 2006). In our case, we placed a factor loading of unit to 5 banks concentration ratio (CR), the Lerner Index (LI), capital adequacy (CA) and the Z-score (ZS). We determined the goodness of fit by employing the Chi square statistics, Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Means Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (RMSR). We exploited these measures to evaluate the different model specifications because they provide alternatives for choosing the most preferred model.

We performed a CFA on bank concentration as a latent construct and its measurement variables, which include the concentration of five banks' assets (CR) and the Herfindahl-Hirschman Index (HH). These variables were allowed to freely correlate with each other but their error terms were mutually exclusive (Brown, 2006). Figure 2 shows the path analysis of the CFA results of bank concentration as the latent construct. To ensure that our model was well identified we placed a factor loading of one on 5 banks' concentration ratio (CR). This is because the concentration ratio of five largest banks is highly correlated to the banking sector as shown in our factor rotation matrix. Our identification results showed that the measurement parameter variables properly identified our model. Our estimation weights of bank concentration as a latent variable in forecasting the measurement variables (concentration ratio of 5 largest banks (CR) and Herfindahl-Hirschman (HH)) was statistically meaningful at P-value less than 0.05. The estimation weight of bank concentration in predicting the HH was estimated at 0.17. This implies that when bank concentration increases by one unit then the banking sector experiences a medium level concentration at 0.17. This outcome is consistent with Galetic and Obravodic (2018) who suggested that bank concentration is medium if it ranges between 0.1 and 0.18. We further conducted goodness of fit on the measurement variables. The outcome shows that our measurement variables have significant factor loadings to represent bank concentration. This is shown in Figure 2.

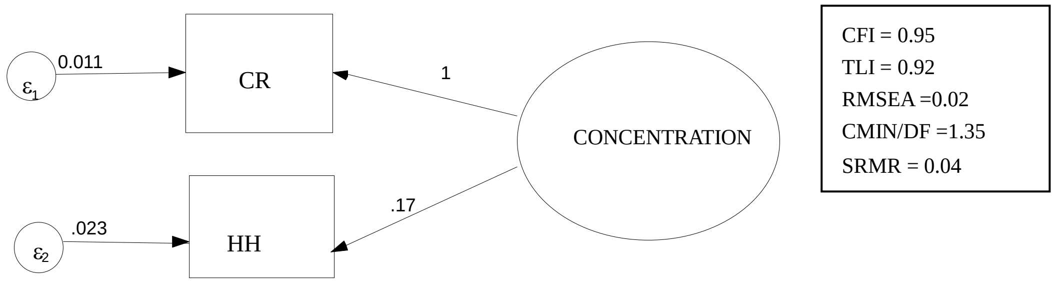


Figure 2. CFA for bank concentration and its observed variables

*Note.* Indicator variables that include concentration ratio of 5 largest banks (CR) and Herfindahl-Hirschman (HH) proxy bank concentration as the latent construct. All the goodness of fit indices is presented in the table at the top right.

We also conducted a path analysis on the measurement variables of competition as our latent construct. Figure 3 presents the CFA results for competition and its observed variables. Competition is estimated using the Boone Indicator (BO), the H-statistics (HS) and the Lerner Index (LI). To ensure that our latent variable is well-identified we set a factor loading of unit on LI. Our evaluation shows that competition as a latent construct in forecasting the measurement variables that include BO and HS were statistically significant. This implies that when competition increases by one unit then BO and HS increase by 0.65 and 0.85 respectively. This is an indication that competition had a significant factor loading (Park, 2013). We further measured the goodness of fit of our model. The estimation result show that the measurement variables that represent the latent variable (competition) have a significant measure of goodness of fit as shown in Figure 3.

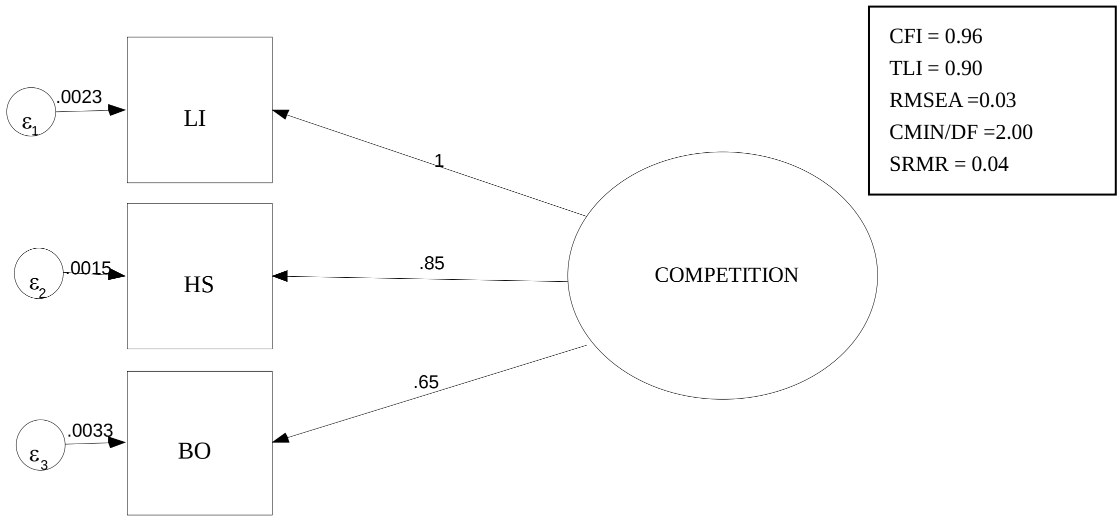


Figure 3. CFA for competition and its observed variables

*Note.* Lerner Index (LI), H-statistics (HS) and Boone Indicator (BO) are exogenous variables that represent bank competition as the latent construct. All the goodness of fit indices is presented in the table at the top right.

We further performed a CFA on bank regulation as a latent exogenous variable as shown in Figure 4. Measurement variables that represent our latent construct include capital adequacy (CA), asset quality (AQ) and debt to operating income ratio (DI). The regression weight of bank regulation in predicting capital adequacy was set at 1 based on the theory that emphasizes on high values of capital adequacy ratio to represent a stable banking system. Our regression weights of bank regulations were statistically significant. This finding is consistent with Bruno, Shim, and Shin (2014). Five goodness of fit tests showed that our model fits well. This implied that our measurement variables were well fit to explain the latent construct (bank regulation).

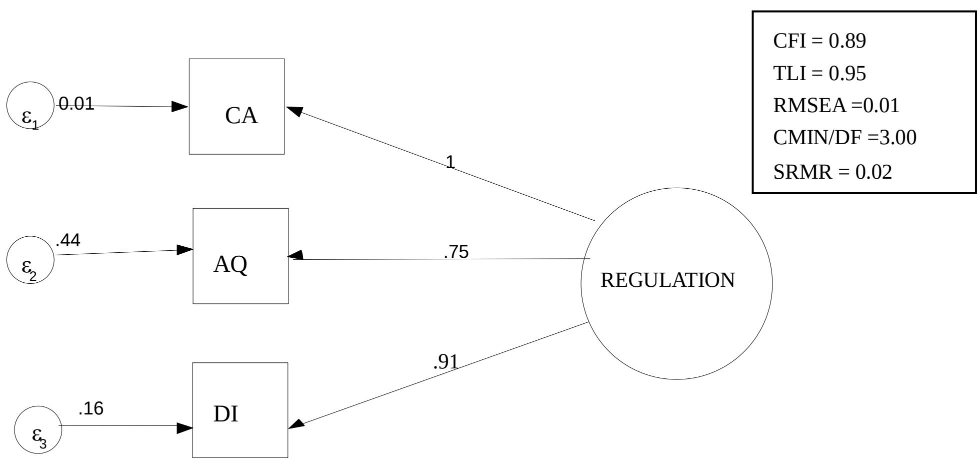


Figure 4. CFA for bank regulations and its observed measurement variables

*Note.* All indicator variables viz. capital asset (CA), asset quality (AQ) and debt to operating income ratio (DI) depict bank regulation as a latent construct. All the goodness of fit indices is presented in the table at the top right.

Finally, we performed a CFA on financial stability as latent exogenous variables and its proxy for observed endogenous variables that include the Z-score (ZS), ratio of credit provision to bank deposit (CB), Standard deviation of banks' lending rate (SL) and standard deviation of banks' deposit rate (SB) and the results presented in Table 5.

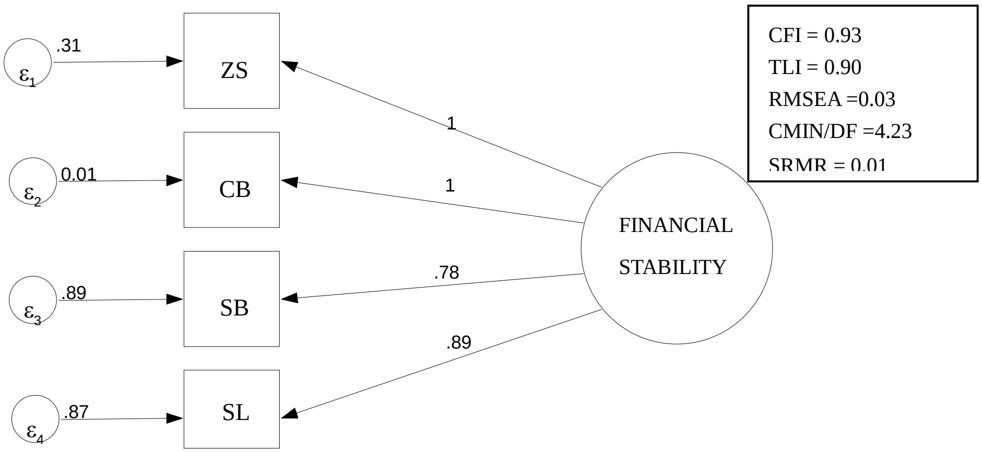


Figure 5. CFA for Financial Stability and its Observed Variables

*Note.* Financial stability as the latent variable is proxied by Bank Z-score (ZS), Ratio of credit provision to bank deposit (CB), standard deviation of banks' lending rate (SL) and Standard deviation of banks' deposit rate (SB). All the goodness of fit indices is presented in the top-right table.

The estimation weight for financial stability in forecasting the Z-score was fixed at 1 in line with theoretical underpinnings (Kline, 2005). The estimation weight for financial stability in projecting CB, SL and SB were all statistically significant. Regression weight of financial stability in forecasting standard deviation of banks' lending rate and standard deviation of banks' deposit rate was estimated at 0.28 and 0.36 respectively. The deviation is not widely spread from zero, which implies that the variation is not so large to impede growth. When the variation is small and positive banks will be able to forecast future returns from lending interest rates and at the same time attract deposits through stable deposit rates (Cihak & Melecky, 2016). The regression weight of financial stability in predicting credit provision was estimated at -0.63. There is evidence therefore that the measurement variables that proxy financial stability have significant factor loadings.

*4.3 Structural Equation Model Results*

The structural link between bank concentration, competition, regulation and financial stability is presented in Figure 6. The unstandardized coefficient trail of: 5-bank assets concentration ratio (CR), the Lerner Index (LI), capital adequacy (CA) and the Z-score (ZS) was constrained to a unit in line with theory (Kline, 2005; Boomsma, 2000). For that reason, there was no test of significance for these four paths. The measurable endogenous variables included: the five banks concentration ratio, Herfindahl-Hirschman Index, Boone Indicator, H-statistics, Lerner Index, capital adequacy, asset quality, debt to income ratio, Z-score, a ratio of credit provision to bank deposit, standard deviation of banks' lending rate and standard deviation of banks' deposit rate. The unobserved measurable endogenous variable comprised of competition and financial stability while the unobserved exogenous measurable variable included bank concentration, bank regulations and the residual terms $\varepsilon_1$ to $\varepsilon_{15}$.

Estimation weight for bank concentration in predicting financial stability was negative and statistically significant. This postulates that higher concentration may induce banks to increase cost of service provision as well as interest rates. This may exacerbate credit risks and expose banks to systemic risks. A higher concentration will further induce banks to undertake risky ventures leading to a moral hazard problem. Our estimation result, therefore, supports the 'concentration-fragility' hypothesis, which is consistent with Feldman (2015).

Variables that proxy bank competition (BO, HS, LI) is positively and significantly related to financial stability (ZS, CB, SB, SL). Our result, therefore, supports the competition-stability channel. Less competition provides an incentive for banks to take excessive risks, which renders the banks vulnerable to systemic risks. Similar findings have been documented by Owen and Pereira (2018). The level of bank concentration in Kenya has therefore enhanced bank competition leading to a stable financial system over time (Mdoe et al., 2019).

When examining the control variables, we discover that regulation positively influences financial stability but impacts negatively on competition. Introducing strict bank regulations that ensure adequate capital and improved asset quality guarantees financial stability. We also establish that better regulation lowers bank competition. When banks are few in the market they may form cartels to control the cost of providing banking services. This thwarts competition and forms a monopoly market which is associated with greater banking system fragility. (Jimez et al., 2013).

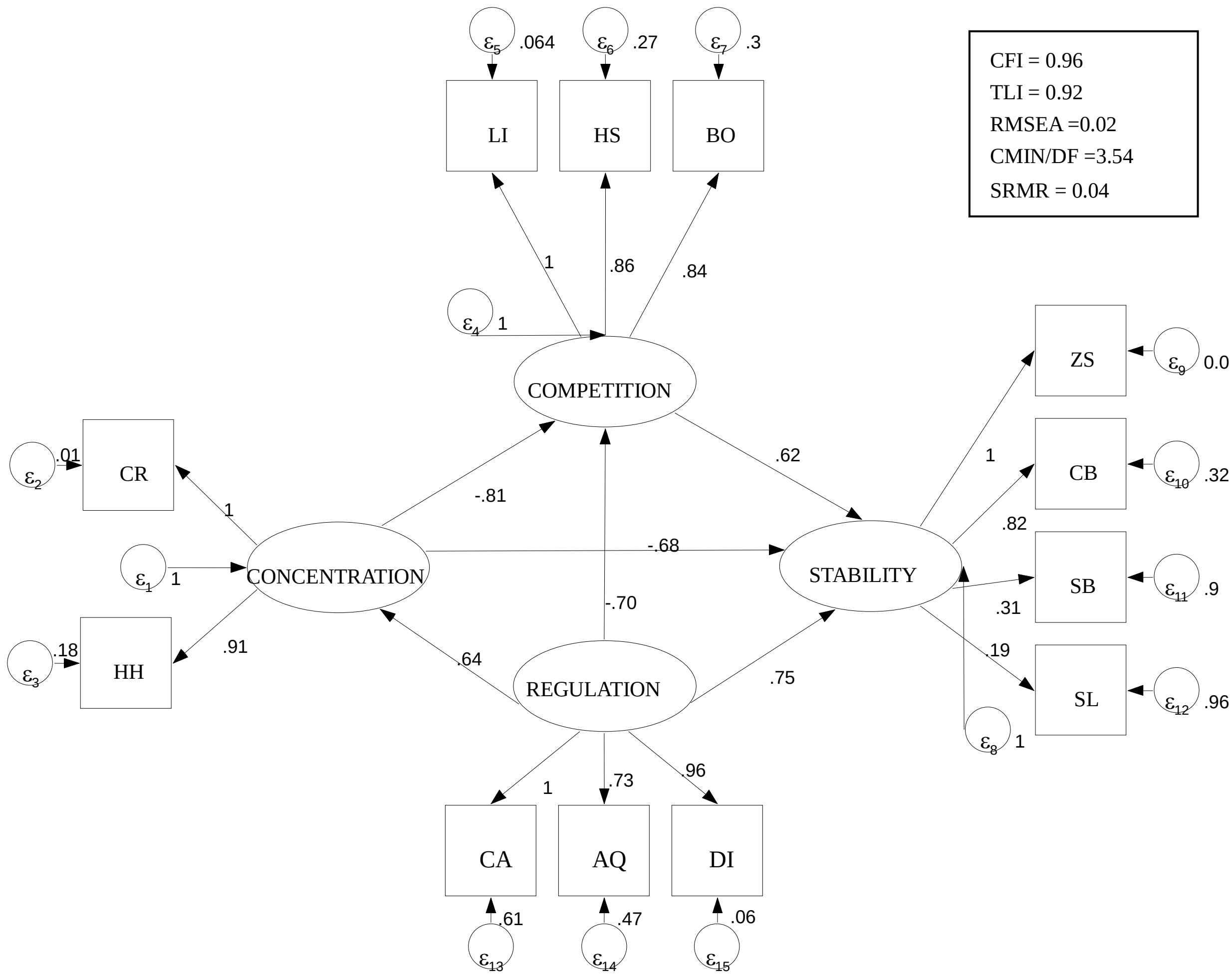


Figure 6. SEM estimation results for bank concentration and financial stability

*Note.* The regression path analysis of SEM shows both the direct and indirect effect of concentration on financial stability in Kenya. The table at the top right shows how best our model is fit to provide valid results.

Table 6 shows the results of the regression path analysis. All the parameter estimates connecting concentration, regulation, competition and financial stability are significant at P<0.05. Further, the regression path linking regulation concentration and competition were significant at P<0.05. Parameter estimates between regulation and concentration were also statistically significant with a probability value of less than 0.05.

Table 6. Results of regression path analysis

| Regression | Estimates | Std. Error | Z-Value | P-Value |
|---|---|---|---|---|
| Stability ←- Concentration | -0.68 | 0.22 | -3.09 | 0.001 |
| Stability ←- Regulation | 0.75 | 0.09 | 8.33 | 0.000 |
| Stability ←- Competition | 0.62 | 0.10 | 6.20 | 0.000 |
| Competition ←- Regulation | -0.70 | 0.08 | -8.75 | 0.000 |
| Competition ←- Concentration | -0.81 | 0.20 | -4.05 | 0.000 |
| Concentration ←- Regulation | 0.64 | 0.07 | 9.14 | 0.000 |

*Note*. The symbol, "←-" means that one latent variable is regressed on the other latent variable.

All the fit indices show that our model fits well for estimation (see Figure 6). This implies that the variance between indicator variables and the latent constructs values are small and unbiased.

## 5. Conclusion

This study sought to explore the link between bank concentration and financial stability with competition as an intervening variable. The novelity of this study lies on the use of structural equation modeling (SEM) in analyzing both direct and indirect effects of bank concentration on financial stability. Unlike other estimation techniques such as GMM and panel data regression, SEM enables us to tackle the problem of approximating measurement errors. The study identifies a series of key findings and policy implications. SEM analysis confirms that the Kenyan banking sector follows the 'concentration-fragility' hypothesis. Thus, higher concentration could induce banks to increase cost of service provision as well as interest rates which may exacerbate credit risks and expose banks to systematic risks. Further, competition plays a significant part in ensuring the stability of the financial system which supports the 'competition-stability' hypothesis. Uncompetitive banking industry may therefore provide incentive for banks to take excessive risks, which renders them vulnerable to systematic risks. We also establish that tight regulations enhances concentration and financial stability but hinders competition. These new insights give bank regulators and policy makers an incentive to formulate and implement the right policies to increase the stability of the financial system.

These results have policy implications for both banks, regulators and policymakers. Central bank should introduce policies that encourage easy entry and exit of banks in the market to reduce concentration. This includes easy registration of both foreign and domestic banks. To boost competition, central bank should enhance activity restrictions and merger review processes of small banks for intermediation efficiency gains. These policy implications are plausible since they are consistent with the legal and regulatory framework governing banks in Kenya. A limitation of this study is that we have not investigated all the mechanisms through which banks' concentration and competition affect financial stability. This could be achieved by incorporating both structural and non-structural measures of bank concentration and competition that are more tailored to individual specific banks.

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