www.cya.unam.mx/index.php/cya

Contaduría y Administración

Accounting & Management

Contaduría y Administración 67 (3), 2022, 1-26

Long-term relation between bank competition and economic growth: An international approach by income level

Relación de largo plazo entre competencia bancaria y crecimiento económico: un enfoque internacional clasificado por nivel de ingreso

Tomas Gómez Rodríguez[1*], Humberto Ríos Bolívar[2], Adriana Zambrano Reyes[1]

[1]Universidad Autónoma del Estado de Hidalgo, México
[2]Instituto Politécnico Nacional, México

Received February 17, 2021; accepted May 11, 2022
Available online October 27, 2022

Abstract

Competition in the banking sector could play a critical role in the long-term economic growth of countries. Therefore, three different measures of competition are used to analyze this relationship: the Lerner index, the Boone index and the concentration index. Gross Domestic Product per capita by purchasing power parity was used as the dependent variable. For each variable, three samples are utilized which are classified into high, middle and low income; following the work of Dayé, Housa and Reding (2016). For the estimation, the following methods were used: Fully Modified Ordinary Least Squares and the Dynamic Ordinary Least Squares method. The results indicate that the high-income and low-income samples for the bank concentration index variable, as well as the low-income sample for the Boone index variable show evidence supporting the market power approach.

JEL Code: C01, C23, G21, L10, O40
Keywords: long-run; cointegration; bank competition; economic growth; international

*Corresponding author.
E-mail address: ya1mx@yahoo.com.mx (T. Gómez Rodríguez).
Peer Review under the responsibility of Universidad Nacional Autónoma de México.

http://dx.doi.org/10.22201/fca.24488410e.2022.3245

Resumen

La competencia en el sector bancario podría jugar un papel crítico en el crecimiento económico de los países a largo plazo. Por tanto, para analizar esta relación se utilizan tres medidas diferentes de competencia: el índice de Lerner, el índice de Boone y el índice de concentración. Como variable dependiente se utilizó el Producto Interno Bruto per cápita por paridad de poder de compra. Para cada variable se utilizan tres muestras las cuales se clasifican en ingreso: alto, medio y bajo; siguiendo el trabajo de Dayé, Housa y Reding (2016). Para la estimación se emplearon los métodos de: Mínimos Cuadrados Ordinarios Completamente Modificados y el método de Mínimos Cuadrados Ordinarios Dinámicos. Los resultados indican que las muestras de alto ingreso y bajo ingreso para la variable índice de concentración bancario, así como la muestra de ingresos bajos para la variable índice de Boone muestran evidencia que apoya el enfoque de poder de mercado.

Código JEL: C01, C23, G21, L10, O40
Palabras clave: largo plazo; cointegración; competencia bancaria; crecimiento económico; internacional

Introduction

Concentration in the banking sector is an ongoing concern, as it affects the performance and efficiency of commercial banks, which could impact investment and economic growth. Likewise, the concentration of funds in key financial institutions can lead to fragility in the financial sector (Fohlin and Jaremski, 2020).

On the other hand, competition is considered one of the market structures with the most desirable characteristics. This is because competition brings benefits such as stimulating innovation, lowering prices, increasing product and service quality, increasing welfare, and accelerating economic growth (Banya and Biekpe, 2017).

Currently, research related to banking competition focuses on two aspects: economic growth and financial stability. The idea that competition in the banking sector is a key factor in obtaining higher growth rates has increased interest in this topic.

Evidence from various studies suggests that countries exhibiting higher levels of competition can obtain higher growth rates and achieve higher per capita income levels than countries exhibiting lower rates of competition. These studies include those of Jayakumar et al. (2018), Diallo and Koch (2018), Coccorese (2017), Banya and Biekpe (2017), Caggiano and Calice (2016), and de Guevara and Maudos (2017). The findings of these studies have prompted the consideration that competition could affect economic growth in the long run.

Specifically, this paper proposes to empirically test the assumption that bank competition promotes economic growth in the long run. In other words, it tests the market power hypothesis in the long run.

To this end, two measures of competition are examined: the Boone index and the Lerner index. The former evaluates market power and the latter measures competition through efficiency. In addition, the banking sector centralization is analyzed through the concentration index of the five most important banks. Gross Domestic Product per capita by purchasing power parity was used as the dependent variable. Three different samples are proposed, three for each variable considered in the study. Each sample contains three subsamples: high, medium and low income. The Fully Modified Ordinary Least Squares (FMOLS) method developed by Pedroni (2000), and the Dynamic Ordinary Least Squares (DOLS) method were used.

This study is organized as follows: the data section describes the variables, the composition of the different samples used and their basic statistics. The methodology section specifies the methodological procedures used. The results section shows the main findings of the econometric estimations, and finally, the conclusions section records the study's contributions.

Literature review

The debate about the effects of bank competition on economic growth is far from being defined. The literature studying the effect of bank competition on economic growth can be classified into two main approaches: the first is the traditional market power approach which argues that the lack of competition in the banking market increases the cost of financing and decreases the availability of financial services (Owen and Pereira, 2018). Moreover, given the absence of competition in the market, it is observed that the number of investment projects that receive financing is lower and therefore, economic growth decreases. Therefore, the fact that the banking sector enjoys market power will reduce incentives to invest in sectors that are more dependent on external financing, thus reducing their potential growth. Some papers supporting this approach include Mitchener and Wheelock (2013), Adu-Asare Idun and Aboagye (2014), Caggiano and Calice (2016), Banya and Biekpe (2017), and Rakshit and Bardhan (2019).

The alternative approach argues that competition can have a negative impact on credit. One of the reasons why this situation may occur is that competition may interact with the level of asymmetric information in the market. That is, this approach argues that competitive banking systems can reduce the creation of relations between credit applicants and banks by reducing the incentive for banks to invest in soft information. Therefore, less competitive markets may be associated with greater credit availability, in line with the work of Petersen and Rajan (1995) and Dell'Ariccia and Marquez (2004). Some papers whose results support the alternative approach are Cetorelli and Gambera (2001), Bonaccorsi di Patti and Dell'Ariccia (2001) and de Guevara and Maudos (2011).

On the other hand, the work of Dayé, Housa, and Reding (2016) argues that lenders need to make the best decisions when choosing projects to be financed. For this purpose, the quality of the information (the company's financial statements, the actual risk of the project, and other characteristics) disclosed by loan applicants is important. Therefore, if the information is of poor quality, opaque or unavailable, as is the case for small and medium-sized companies, lenders will be more reluctant to finance them. This can lead to some information asymmetries, such as the adverse selection problem, which would mean that some less risky and good quality projects are displaced by poorer quality and riskier projects. To avoid this situation, borrowers and loan applicants have developed several coping strategies. One such strategy is to minimize the cost of obtaining information through centralizing information in public credit registries and private credit bureaus. Specifically, the existence of private credit bureaus has been found to significantly reduce information asymmetries, according to Triki and Gajigo (2014). However, this institution is absent in many countries, especially developing ones (Dayé, Housa, and Reding, 2016).

Separately, the work of Ajisafe and Ajide (2014) analyzes the long-term relation between competition in the banking sector and economic growth in Nigeria, using the period 1986-2012. They use the vector error correction method to perform the short-term analysis. They employ the banking concentration ratio as a variable to measure banking competition and performed Johansen's cointegration test to examine the existence of a long-term relation in the model. The results of the study show that bank competition has a positive effect on growth both in the short run, according to the results of the vector error correction model, and in the long run, as suggested by the cointegration test and the likelihood ratio test.

In this context, this research extends the existing literature in the following points: 1) By analyzing the relation between competition in the banking sector and long-run economic growth using panel data techniques. 2) The sample is divided into low, middle and high-income countries to empirically analyze whether asymmetric information problems derived from the absence of private credit bureaus—following the work of Dayé, Housa and Reding (2016)—can affect the relation between competition and economic growth. And 3) Three different samples are proposed, three for each variable considered in the study; these samples are composed of 112, 86, and 110 countries.

Data

The database consists of three different samples. The countries in each sample are classified according to their income into three classes: high, middle, and low. The classification was made according to a World Bank standard, except that the upper middle-income and lower middle-income classes were merged into a single class, called middle income. The first sample is constituted by two variables, the Gross Domestic

Product per capita expressed in purchasing power parity at constant 2011 prices (GDPppp) as the dependent variable and the Boone index (Boone) as the independent variable. The period considered covers 1999 to 2014. The number of countries that make up this sample is 112 countries. The second sample comprises the variable (GDPppp) as the dependent variable and the Lerner index (Lerner) as the independent variable; the period to be examined is from 1996 to 2014. This sample is composed of 86 countries. Finally, the third sample comprises the variables (GDPppp) and the bank concentration index of the three most important banks (Concentration); the period under study is from 1996 to 2017. For this sample, data were obtained from 110 countries.

Different study periods are used in each sample since data for countries are not available for the calculation of competition indices in each sample; therefore, the selection of the period to be studied was made considering this situation. Consequently, nine panels of unbalanced data are considered, three for each sample, as shown in Table (1). The list of countries that make up each panel is also indicated. It is worth mentioning that these tables and lists can be found in the Appendix section.

Table 1
Number of countries per sample

Sample	Number of countries	List
Boone		
Boone high income	46	1a
Boone medium income	58	2a
Boone low income	8	3a
Lerner		
Lerner high income	40	4a
Lerner medium income	42	5a
Lerner low income	4	6a
Concentration		
Concentration high income	48	7a
Concentration medium income	56	8a
Concentration low income	6	9a

Source: created by the authors

One of the first market concentration indicators to consider is the concentration index, defined as the sum of the market shares of the largest firms in the market (Lijesen, Nijkamp and Rietveld, 2002). Therefore, the concentration index is calculated as follows:

$$CR_m = \sum_{i=1}^{m} S_i \tag{1}$$

Where S_i is the market share for each bank. If the concentration index for the five largest banks is less than 50%, the banking sector is considered to be competitive.

The Lerner index represents the margin of price over marginal costs and is an indicator of the degree of market power. It is also an indicator of the proportion "level" by which price exceeds the marginal cost and is calculated as follows:

$$\mathrm{Lerner}_{it} = (\mathrm{PTA}_{it} - \mathrm{MCTA}_{it})/\mathrm{PTA}_{it} \tag{2}$$

Where PTA_{it} is financial revenues between total assets for bank i and time t and MCTA_{it} is the marginal cost of total assets for bank i and time t. If the value of the Lerner index is 0, it is assumed that the market is in perfect competition; if the Lerner index is 1, the market is in a monopoly; and between 0 and 1, the market shows monopolistic competition.

The Boone index, presented by Schaeck and Cihák (2013), is manifested as the elasticity of profits with respect to marginal costs. It is expressed as follows:

$$\pi_{it} = \alpha + \beta \ln(c_{it}) \tag{3}$$

Where π_{it} measures the profits in bank i at time t. β is the Boone indicator, a is the market size, and c_{it} denotes marginal costs.

The rationale behind the indicator is that more efficient companies earn higher profits. Therefore, when the Boone index is negative, it points to greater competition because the repositioning effect is greater. The information for the Lerner, Boone, and $\mathrm{Concentration}$ variables comes from the Global Financial Development Database, whereas the data for the GDPppp variable comes from the World Development Indicators database.

http://dx.doi.org/10.22201/fca.24488410e.2022.3245

Table 2
Variables

Variable	Abbreviation	Source
Gross Domestic Product per capita; purchasing power parity	GDPppp	World Development Indicators
Boone Index	Boone	Global Financial Development Database
Lerner Index	Lerner	Global Financial Development Database
Concentration index of the five largest banks	Concentration	Global Financial Development Database

Source: created by the authors

Tables (3), (4) and (5) show the descriptive statistics for the samples: Boone, Lerner, and Concentration, respectively.

Table 3
Descriptive statistics for the Boone sample

Variable	Mean	Standard deviation	Maximum	Minimum	Observations
Boone high income					
Boone	−1.5	14.1	11.3	−281.2	727
GDPppp	39,539.7	21,990.9	134,959.9	10,480.7	735
Boone medium income					
Boone	−0.1	0.2	1.7	−2.5	903
GDPppp	8,652.5	5,322.4	29,493.8	1,278.9	928
Boone low income					
Boone	−0.02	0.06	0.2	−0.1	120
GDPppp	1,329.06	445.9	2,385.4	602.7	128

Source: created by the authors

Table 4
Descriptive statistics for the Lerner sample

Variable	Mean	Standard deviation	Maximum	Minimum	Remarks
Lerner high income					
Lerner	0.2	0.1	1.07	−1.1	744
GDPppp	36,614.3	18,678.7	134,959.9	8,589.6	760
Lerner medium income					
Lerner	0.2	0.1	0.6	−0.6	773
GDPppp	8,891.5	5200	25,551.09	1,516.1	798
Lerner low income					
Lerner	0.3	0.1	0.5	0.03	83
GDPppp	1,269.6	479.8	2,385.4	589.9	95

Source: created by the authors

Table 5
Descriptive statistics for the Concentration sample

Variable	Mean	Standard deviation	Maximum	Minimum	Remarks
		Concentration high income			
Concentration	68.9	17.9	100	20.1	1033
GDPppp	38,814.6	21,344.1	134,959.9	8,589.6	1052
		Concentration medium income			
Concentration	59.8	16.6	100	20.8	1194
GDPppp	9,225.7	5,494.06	29,493.8	1,516.1	1229
		Concentration low income			
Concentration	71.6	21.3	100	17.1	123
GDPppp	1,340.8	465.4	2,613.1	670.7	132

Source: created by the authors

Methodology

Three different measures of competition are used to analyze the long-run relation between competition in the banking sector and economic growth: the Lerner index, the Boone indicator, and the bank concentration index for the three most important banks. Based on the above, the following models are proposed to analyze the long-term relation between competition in the banking sector and economic growth:

$$\mathrm{GGDPppp_{it}} = \beta_0 + \beta_1 \mathrm{Boone} + e_{i,t} \tag{4}$$

$$\mathrm{GGDPppp_{it}} = \beta_0 + \beta_1 \mathrm{Lerner} + e_{i,t} \tag{5}$$

$$\mathrm{GGDPppp_{it}} = \beta_0 + \beta_1 \mathrm{Concentration} + e_{i,t} \tag{6}$$

These three models will be estimated three times, once for each income level. The cross-sectional dependence test is performed for all variables as a first step to test for the existence of this relation. The first- and second-generation unit root tests are performed in the second step. The third step consists of estimating the Pedroni panel cointegration test. Finally, the FMOLS and DOLS methods to estimate three different models are used, one for each measure of competition.

http://dx.doi.org/10.22201/fca.24488410e.2022.3245

Cross-sectional dependence test

The existence of common shocks among the countries included in the panel could generate a contemporaneous correlation; this situation is also known as cross-sectional dependence. Since the existence of cross-section dependence can result in forecast errors, it is crucial to diagnose this problem before estimating panel data models (Vural, 2020).

Therefore, the following null hypothesis is tested: the residuals of the standard panel regression are not correlated at the same time. Consequently, a diagnosis is carried out to determine whether the pairwise covariance among the residuals is zero. That is:

$$H_0 := p_{ij} = p_{ji} = \mathrm{Cov}(\varepsilon_{it}, \varepsilon_{jt}) = 0, \text{para todo } t, i \neq j \tag{7}$$

$$H_1 := p_{ij} = p_{ji} = \mathrm{Cov}(\varepsilon_{it}, \varepsilon_{jt}) \neq 0, \text{for all } t, i \neq j \tag{8}$$

The Pesaran cross-sectional dependence test (Pesaran, 2004), or CD test, is applied to test the above hypotheses. This test is considered the most general since it can be used for both stationary and non-stationary panels. Moreover, it has reasonable properties for small samples (Abdullah, Siddiqua, & Huque, 2017). Pesaran's CD test is expressed as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}\right) \tag{9}$$

Where T is the time dimension, N is the section dimension, and $\hat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of the residuals.

Unit root test for panel

The unit root test based on panel data is performed since it has better properties than the test using individual time series. The existence of independence in the cross-section is a crucial assumption for all available unit root tests. However, the Im, Pesaran, and Shin (IPS) panel unit root test relaxes the restrictive assumptions of no serial correlation and panel homogeneity. This test uses a demeaning procedure (subtracting the group mean from the data) to discover the contemporaneous correlation of the data. Therefore, the IPS test is used in conjunction with the Levin, Lin and Chu (LLC), Breitung, ADF-Fisher, and PP-Fisher tests to detect the stationarity of the variables. In addition, the second-generation test proposed by Pesaran (2007), called the Dickey Fuller augmented cross section (CADF) test, is also used, showing robust results when cross-section dependence is considered. The CADF test is denoted in the following equation:

$$\Delta y_{it} = a_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_{t-1} + \sum_{j=0}^{p} n_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} \tag{10}$$

Where $\bar{y} = N^{-1} \sum_{j=1}^{N} y_{it}$. As the first requirement to prove the existence of a long-run relation, the variables must present an integration of order one I(1). That is, it is expected that the variables do not exhibit a unit root in levels, and in first differences, they show a unit root.

Panel cointegration test

There are different options for the cointegration test; among these are the McCoskey and Kao, Pedroni, Kao, Westerlund, and Fisher tests. The Pedroni Cointegration test for panel data is used to detect the cointegration relation between variables. The reason for this choice is that the Pedroni test allows for heterogeneity.

The Pedroni cointegration test is based on the Engle-Granger test and considers heterogeneous intercepts and trend coefficients across countries. Three regressions are estimated, one for each variable used to conduct the test:

$$GDPppp_{i,t} = \alpha_i + \phi_i t + \gamma_1 Boone_{i,t} + e_{i,t} \tag{11}$$

$$GDPppp_{i,t} = \alpha_i + \phi_i t + \gamma_1 Lerner_{i,t} + e_{i,t} \tag{12}$$

$$GDPppp_{i,t} = \alpha_i + \phi_i t + \gamma_1 Concentration_{i,t} + e_{i,t} \tag{13}$$

Where $i = 1.2.\dots N$ is the number of countries, and $t = 1.2.\dots T$ is the time dimension. This test is performed once it has been proven that the $GDPppp$, $Boone$, $Lerner$, and $Concentration$ variables

http://dx.doi.org/10.22201/fca.24488410e.2022.3245

are assumed to be integrated of order one I(1). Once the regressions have been performed, the residuals are obtained, and an ADF test is performed on the residuals to estimate whether they are I(1) using the following regression test for each country:

$$\Delta e_{i,t} = \rho_{it} e_{i,t-1} + \sum_{j=1}^{p_i} \psi_{i,j} \Delta_{i,t-1} + \upsilon_{i,t} \tag{14}$$

Based on several methods, Pedroni provides eleven statistics divided into two groups, panel statistics (dimension within) and group statistics (dimension between). This method is used to test the hypothesis of no cointegration against its alternative hypotheses.

$$H_0 : \rho_i = 0 \text{ (No cointegration)} \tag{15}$$

$$\text{Homogeneous Alternative}, H_1 : (\rho_i = \rho) < 1 \forall i \tag{16}$$

$$\text{Heterogeneous Alternative}, H_1 : \rho_i < 1 \forall i \tag{17}$$

In particular, the panel statistics are associated with the homogeneous alternative, while the group statistics correspond to the heterogeneous alternative. However, all these statistics are distributed as asymptotically normal.

FMOLS and DOLS

In the samples used, the variables $\mathrm{GGDPppp}$, Boone, Lerner, and $\mathrm{Concentration}$ may present endogeneity problems and their error terms may be serially correlated, which could result in biased estimators when the Ordinary Least Squares method is used. The Fully Modified Ordinary Least Squares method (FMOLS) and the Dynamic Ordinary Least Squares (DOLS) method are considered to solve these problems. Phillips and Hansen (1993) proposed a semi-parametric correction for the long-run correlation problem between the cointegrating equation and the stochastic regressors' innovations, resulting in unbiased asymptotically FMOLS estimators. On the other hand, Saikkonen (1992) and Stock and Watson (1993) developed an asymptotically efficient estimator that eliminates the feedback in the cointegrating system by augmenting the regression with lags and leads of the independent variables. This estimator is known as Dynamic Ordinary Least Squares.

The FMOLS estimator considers the following fixed effects model:

$$GGDPppp_{i,t} = \alpha_i + x'_{i,t}\beta + e_{i,t} \tag{18}$$

Where $i = 1,2....N$ is the number of countries, $t = 1,2....T$ is the time dimension, $GGDPppp_{i,t}$ is the annual growth of Gross Domestic Product per capita per purchasing power parity (an I(1) process), β is a (2*1) vector of parameters, α_i is the intercept, and $e_{i,t}$ is the stationary disturbance term. Here, $x_{i,t}$ is assumed to be a (2*1) vector of independent variables ($\mathrm{Boone, Lerner, and\ Concentration}$), which are I(1). It is assumed to follow an autoregressive process as follows:

$$x_{i,t} = x_{i,t-1} + \epsilon_{i,t} \tag{19}$$

$$\text{Innovation Vector}, W_{i,t} = (u_{i,t}, \varepsilon_{i,t})$$

Since $W_{i,t} = (u_{i,t}, \varepsilon_{i,t}) \sim I(0)$, the variables are said to be cointegrated for each panel member with the cointegrating vector β. The asymptotic distribution of the Ordinary Least Squares estimator is conditional on the long-run covariance matrix of the innovation vector. Therefore, the FMOLS estimator is derived by making the endogeneity correction (by modifying the variable $GGDPppp$) and the serial correlation correction (by modifying the long-run covariance of the innovation vector, $W_{i,t}$). The resulting estimator is expressed as follows:

$$\widehat{\beta}_{FMOLS} = \left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)'\right]^{-1} * \left[\sum_{i=1}^{N}\left(\sum_{t=1}^{T}(x_{it} - \bar{x}_i)\,GG\widehat{DP}ppp_{it} - T\hat{\Delta}_{\varepsilon u}\right)\right] \tag{20}$$

On its part, the DOLS method considers forward data and lagged differences to the $GGDPppp$ variable and other independent variables in the cointegrating regression to control for the endogeneric problem. Forward data and lagged differences are also included to control the serial correlation problem. Due to the above, the equation to be estimated using the DOLS method framework is expressed as follows:

$$GGDPppp_{it} = \alpha_i + \beta_i x_{it} + \sum_{k=-p_1}^{p_2} \delta_k \Delta GGDPppp_{it-k} + \sum_{k=-q_1}^{q_2} \lambda_k \Delta x_{it-k} + e_{it} \tag{21}$$

Results

In order to determine the appropriate estimation method, it is necessary to test whether the variables are stationary or non-stationary and their order of integration. Likewise, the cross-sectional dependence or cross-sectional correlation must also be considered for the variables used in the study to decide which unit root test for panel data to apply.

Table 6
Results of the cross-sectional dependence test

	Pesaran CD Test		
H_0: No cross − sectional dependence			
Variables	High income	Medium income	Low income
Boone	5.770090****	22.59491***	2.872080***
	(0.0000)	(0.0000)	(0.0041)
GDPppp	90.47730****	151.2389***	10.83587***
	(0.0000)	(0.0000)	(0.0000)
Lerner	32.95945***	12.31276***	−2.380823**
	(0.0000)	(0.0000)	(0.0173)
GDPppp	74.33172***	108.6876***	9.805394***
	(0.0000)	(0.0000)	(0.0000)
Concentration	5.770090***	22.59491***	2.872080***
	(0.0000)	(0.0000)	(0.0041)
GDPppp	90.47730***	151.2389***	10.83587***
	(0.0000)	(0.0000)	(0.0000)

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%. The probability is shown in parentheses.
Source: created by the authors

Table (6) contains the results of the test for cross-sectional dependence in the variables used. The results suggest that it is possible to reject the null hypothesis for all variables at 1% significance level in most cases. Therefore, the residuals from the standard panel regression will be correlated simultaneously, which should be addressed while performing the unit root tests forX panel.

The Levin, Lin, and Chu(LLC) test developed by Levin et al. (2002), Breitung, Im, Pesharan and Shin (IPS), the ADF − Fisher and PP − Fisher tests, developed by Choi (2001), and the CADF test are used to test the stationarity of the variables. The CADF test is a second-generation test that allows cross-sectional dependence to be considered.

The IPS, ADF − Fisher and PP − Fisher tests are related to the null hypothesis "panels contain an individual unit root," while the LLC and Breitung tests examine the null hypothesis "panel contains a common unit root." The variables must exhibit non-stationarity in levels and be stationary in first

http://dx.doi.org/10.22201/fca.24488410e.2022.3245

differences to be first-order integrated I(1). If the variables are first-order integrated I(1), one can proceed to test for the long-run relation of cointegration. Unit root tests were carried out using the specification for regression that incorporates intercept and trend. Tables (7), (8), and (9) present the unit root test results for the countries that exhibit evidence of first-order integration I(1).

Table 7
Unit root test for low-income countries for Boone variable

Sample: Boone low income
Countries: 8
Intercept and trend

Variables	LLC	Breitung	IPS	ADF −Fisher	PP −Fisher	CADF
	t^* −statistic	t −statistic	W −statistic	Chi −square	Chi −square	Z (t − bar)
Level						
Boone	2.72896	−0.69295	0.32642	11.8777	36.5250***	−0.959
	(0.1668)	(0.2442)	(0.6279)	(0.7524)	(0.0024)	(0.169)
GDPppp	−0.96683	3.10320	0.23386	19.7536	15.5371	1.046
	(0.1668)	(0.9990)	(0.5925)	(0.2315)	(0.4857)	(0.852)
First differences						
Boone	−0.87650	−1.07907	−0.38836	19.4788	76.1010***	−5.319***
	(0.1904)	(0.1403)	(0.3489)	(0.2446)	(0.0000)	(0.000)
GDPppp	−2.73413***	−0.88187	−2.68341***	34.2156***	83.3473***	−4.766***
	(0.0031)	(0.1889)	(0.0036)	(0.0051)	(0.0000)	(0.000)

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%. The probability is shown in parentheses.
Source: created by the authors

Table (7) presents the results of the unit root tests, which show that GDP PPP and Boone are non-stationary in levels, but become stationary in first differences; therefore, they are integrated of first order I(1). As for the tests in levels, only the PP − Fisher test shows evidence against the Boone variable being non-stationary. Meanwhile, for the GDPppp variable, all tests point to the variable being stationary. The PP − Fisher and CADF tests in first differences for the Boone variable provide evidence in favor of the variable being stationary. Although only two tests out of six provide evidence that the variable is stationary, it was considered that the CADF test, which takes into account the cross-sectional dependence, should have more weight. The results of this test show evidence that the variable is stationary. For the GDPppp variable, only the Breitung test exhibits evidence against GDPppp being stationary. Therefore, the Pedroni cointegration test is performed for this sample.

Table 8
Unit root test for low-income countries for the Concentration variable

Sample: Concentration low income Countries: 6 Intercept and trend						
Variables	LLC t^* −statistic	Breitung t −statistic	IPS W −statistic	ADF −Fisher Chi −square	PP −Fisher Chi −square	CADF Z (t − bar)
Level						
Concentration	-2.85667^{***} (0.0021)	-1.50929^{*} (0.0656)	−1.11856 (0.1317)	18.6604^{*} (0.0971)	22.2580^{**} (0.0347)	−0.101 (0.460)
GDPppp	0.07978 (0.5318)	2.01841 (0.9782)	1.08266 (0.8605)	7.40846 (0.8295)	6.38100 (0.8957)	2.778 (0.997)
First differences						
Concentration	-4.89536^{***} (0.0000)	-4.57880^{***} (0.0000)	-3.18817^{***} (0.0007)	37.0291^{***} (0.0002)	75.0660^{***} (0.0000)	-4.749^{***} (0.000)
GDPppp	-3.76457^{***} (0.0001)	-1.82466^{**} (0.0340)	-2.50948^{***} (0.0060)	26.7963^{***} (0.0083)	47.3180^{***} (0.0000)	-4.684^{***} (0.000)

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%. The probability is shown in parentheses.
Source: created by the authors

Table (8) shows the results of the unit root tests for the sample of low-income countries. The LLC, Breitung, ADF − Fisher, and PP − Fisher tests provide evidence in favor of the Concentration variable being stationary, while the IPS and CADF tests indicate that the variable is non-stationary. As in the previous case, more importance is given to the CADF test; therefore, the Concentration variable is considered non-stationary in level. On the other hand, all the level tests indicate that GDPppp is non-stationary. Likewise, the first differences tests indicate that the Concentration and GDPppp variables are stationary. Therefore, the condition that the variables are non-stationary in levels and stationary in first differences is fulfilled.

http://dx.doi.org/10.22201/fca.24488410e.2022.3245

Table 9
Unit root test for high-income countries for the Concentration variable

Sample: Concentration high income
Countries: 48
Intercept and trend

Variables	LLC	Breitung	IPS	ADF −Fisher	PP −Fisher	CADF
	t^* −statistic	t −statistic	W −statistic	Chi −square	Chi −square	Z (t − bar)
Level						
Concentration	−1.92413**	1.22593	−0.27978	119.577*	112.984	−0.383
	(0.0272)	(0.8899)	(0.3898)	(0.0519)	(0.1136)	(0.351)
GDPppp	4.56781***	−3.15481***	−1.16366	107.279	55.7209	4.073
	(0.0000)	(0.0008)	(0.1223)	(0.2028)	(0.9997)	(1.000)
First differences						
Concentration	−3.57108***	−3.68281***	−8.94329***	261.333***	730.030***	−17.509***
	(0.0002)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.000)
GDPppp	−10.6652***	−8.73042***	−6.42453***	198.962***	264.504***	−4.557***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000)

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%. The probability is shown in parentheses.
Source: created by the authors

Table (9) shows the results of the unit root tests for the sample of high-income countries for the Concentration variable. The level tests that find evidence against the Concentration variable being non-stationary are LLC and ADF − Fisher; the rest of the tests point to the Concentration variable being non-stationary. As for the GDPppp variable, the IPS, ADF − Fisher, PP − Fisher and CADF tests show that it is non-stationary in level. The first difference tests for both variables show that both are stationary. In this case, it is found that the cointegration test can be performed between the selected variables because they are integrated of first order.

In order to test for cointegration between GDPppp and the variables measuring the level of competition, the Pedroni cointegration test for panel data is used. This test is performed for the following samples: Boone low income, Concentration low income, and Concentration high income. The test was performed with three deterministic specifications: intercept, intercept and trend, and no intercept and no trend. Tables (10), (11) and (12) present the results of the test using the intercept and trend specification.

Table 10
Pedroni cointegration test with intercept and trend for the Boone low income sample

Sample: Boone low income Intercept and trend				
	Statistic	Probability	Weighted statistic	Probability
Panel v	0.499856	(0.3086)	−1.218261	(0.8884)
Panel rho	−0.934889	(0.1749)	−1.091422	(0.1375)
Panel PP	−2.829097***	(0.0023)	−3.549629***	(0.0002)
Panel ADF	2.438929	(0.9926)	−0.621665	(0.2671)
Group rho	−0.308978	(0.3787)		
Group PP	−4.792453***	(0.0000)		
Group ADF	−0.458294	(0.3234)		

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%.
Source: created by the authors

The results of the cointegration test for the sample of low-income countries for the Boone variable with the intercept and trend specification are shown in Table (10). In this specification, the hypothesis of no correlation is rejected for eight out of eleven statistics. In the deterministic specification with intercept, the hypothesis of no correlation is rejected in one out of eleven statistics. In the third deterministic specification without intercept and trend, four out of eleven statistics reject the hypothesis of no correlation. Therefore, the results indicate that out of three specifications, the hypothesis of correlation is accepted in two.

Table 11
Pedroni cointegration test with intercept and trend for the Concentration low income sample

Sample: Concentration low income Intercept and trend				
	Statistic	Probability	Weighted statistic	Probability
Panel v	0.276531	(0.3911)	−1.580707	(0.9430)
Panel rho	−0.141203	(0.4439)	−1.182825	(0.1184)
Panel PP	−1.482679*	(0.0691)	−2.940319***	(0.0016)
Panel ADF	−1.432130*	(0.0761)	−3.510098***	(0.0002)
Group rho	0.602109	(0.7264)		
Group PP	−1.832517**	(0.0334)		
Group ADF	−2.257041**	(0.0120)		

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%.
Source: created by the authors

Table (11) shows the results of the Pedroni cointegration test for the low-income sample with the Concentration variable. The results show that five out of eleven statistics reject the hypothesis of no correlation. As for the specification with intercept, three out of eleven statistics reject the hypothesis of

http://dx.doi.org/10.22201/fca.24488410e.2022.3245

no correlation. The results of the specification without intercept and trend show that all statistics reject the hypothesis of correlation. Consequently, two out of three specifications indicate that correlation exists.

Table 12
Pedroni cointegration test with intercept and trend for the Concentration high income sample

Sample: Concentration high income				
Intercept and trend				
	Statistic	Probability	Weighted statistic	Probability
Panel v	−1.555578	(0.9401)	−4.456452	(1.0000)
Panel rho	−1.365394*	(0.0861)	−0.741187	(0.2293)
Panel PP	−4.783145***	(0.0000)	−5.107233***	(0.0000)
Panel ADF	−4.222028***	(0.0000)	2.864839***	(0.0021)
Group rho	0.924684	(0.8224)		
Group PP	−5.441888***	(0.0000)		
Group ADF	−2.528440***	(0.0057)		

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%.
Source: created by the authors

Table (12) contains the results of the Pedroni cointegration test for the high-income sample with the Concentration variable. The results of the deterministic specification, including intercept and trend, show that six out of eleven statistics lead to a rejection of the hypothesis of no correlation. In the deterministic specification, including intercept, nine out of eleven statistics provide evidence against the hypothesis of no correlation. The specification that considers a deterministic model without trend or intercept rejects the hypothesis of no correlation in three out of eleven statistics. Therefore, two out of three specifications provide evidence against the hypothesis of no correlation.

The results of the Pedroni test allow arguments in favor of a cointegration relation for the three samples analyzed: Boone low income, Concentration low income, and Concentration high income.

In order to estimate the long-run coefficient for the samples above, the Fully Modified Ordinary Least Squares (FMOLS) method, developed by Pedroni (2000), and the Dynamic Panel Least Squares (DOLS) method are used. Each of these methods has three different estimators: pooled, weighted pooled, and pooled mean. In this research, the weighted pooled estimator proposed in the works of Pedroni (2001) and Kao and Chiang (2000) was used, which allows for different long-run variations among the cross-section for heterogeneous panels. Moreover, the DOLS method is an extension of the model with lags and leads of the differences between the dependent and independent variables and makes it possible to overcome the problem of asymptotic endogeneity and serial correlation. As with the FMOLS method, the weighted estimator developed by Mark and Sul (2003) is used, which allows for heterogeneous variation in the long run.

Table 13
Estimation results with FMOLS and DOLS methods for the Boone low income sample

FMOLS			
Independent variable	Coefficient	Statistic-t	Probability
Boone	-34.01313^{***}	-305.3984	(0.0000)
Statistics			
R-squared	0.842033		
DOLS			
Independent variable	Coefficient	Statistic-t	Probability
Boone	-212.9264	-0.849638	(0.3991)
Statistics			
R-squared	0.897403		

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%.
Source: created by the authors

Table (13) shows the results of the estimations with the FMOLS and DOLS methods for the Boone low income sample. The results show a positive long-run relation between the level of competition measured by the Boone index and economic growth when the FMOLS method is considered. A 1% increase in the Boone variable would mean a 34-dollar decrease in the GDPppp variable. The Boone variable is statistically significant. It is worth mentioning that negative values of the Boone variable mean more competition, so an increase in this variable would mean less competition. The results of the DOLS method indicate that the Boone variable is not statistically significant.

Table 14
Estimation results with the FMOLS and DOLS methods for the Concentration low income sample

FMOLS			
Independent variable	Coefficient	Statistic-t	Probability
Concentration	-14.67227^{***}	-448.6701	(0.0000)
Statistics			
R-squared	0.878444		
DOLS			
Independent variable	Coefficient	Statistic-t	Probability
Concentration	-14.39543^{***}	-5.790334	(0.0000)
Statistics			
R-squared	0.927270		

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%.
Source: created by the authors

The results of the estimations with the FMOLS and DOLS methods for the Concentration low-income sample are shown in Table (14). In both estimations, a negative relation between GDPppp and Concentration is found. The estimation using the FMOLS method indicates that a 1% increase in the Concentration variable implies a 14.6 dollar decrease in the GDPppp variable. Conversely, the estimation using the DOLS method indicates that a 1% increase in the variable means a decrease of 14.3 dollars in the GDPppp variable. In both estimation models, the Concentration variable is statistically significant at 1%.

Table 15
Estimation results with the FMOLS and DOLS methods for the Concentration high income sample

FMOLS			
Independent variable	Coefficient	Statistic-t	Probability
Concentration	-49.88484^{***}	-2296.319	(0.0000)
Statistics			
R-squared	0.897826		
DOLS			
Independent variable	Coefficient	Statistic-t	Probability
Concentration	-108.2681^{***}	-4.999600	0.0000)
Statistics			
R-squared	0.92		

Note: *** indicates a significance level of 1%, ** means a significance level of 5% and * denotes a significance level of 10%.
Source: created by the authors

The estimation results for the Concentration high income sample are shown in Table (15). In both FMOLS and DOLS estimations, a negative relation between Concentration and GDPppp is found. A 1% increase in the Concentration variable suggests a 49.8 dollar reduction in the GDPppp variable according to the FMOLS estimation results. Meanwhile, the DOLS estimation results indicate that a 1% increase in the Concentration variable would mean a decrease of 108 dollars in the GDPppp variable. Both variables are statistically significant at 1% in the two estimations used.

Consequently, the results for the Concentration low income and Concentration high income samples exhibit a negative relation between Concentration and GDPppp. The growth-reducing effect is greater in the Concentration high income sample, while the results for the Boone low income sample indicate a positive relation between competition and GDPppp. It is important to highlight that of the estimation methods, in only one is the coefficient statistically significant for this sample.

Conclusions

Nine samples were studied, three for each market structure measure. First, Pesaran's CD test was performed to look for evidence of cross-sectional codependence. The results show evidence in favor of the presence of cross-sectional dependence for all variables. For this reason, in addition to using the first generation LLC, Breitung, IPS, ADF – Fisher, and PP – Fisher tests, the second generation CADF test was used, which considers cross-sectional dependence. The results of the unit root tests show evidence of first-order integration I(1) for the samples: Boone low income, Concentration low income, and Concentration high income.

Consequently, Pedroni cointegration tests were performed for these three samples. Evidence was found to favor a long-term cointegration relation for all three samples. Finally, estimations were performed using the FMOLS and DOLS methods. Evidence of a negative long-term relation of cointegration between the level of bank concentration and economic growth was found for the Concentration low income and Concentration high income samples. These results are consistent with the theoretical prediction that more bank competition translates into higher economic growth. Therefore, the evidence found supports the market power approach. Similarly, a positive long-run cointegration relation was found between efficiency, as measured by the Boone index, and economic growth. The evidence comes from the Boone low income sample. This result also supports the market power approach.

On the other hand, the results of the three samples, Concentration low income, Concentration high income and Boone low income are consistent with the findings of the works of Mitchener and Wheelock (2013), Adu-Asare Idun and Aboagye (2014), Caggiano and Calice (2016), Banya and Biekpe (2017), and Rakshit and Bardhan (2019). Meanwhile, in the work of Ajisafe and Ajide (2014), which studies the relation between competition in the banking sector and economic growth in the case of Nigeria, both short-term and long-term estimation techniques are employed. Their results show that in both the short and long run, the relation between banking competition and economic growth is positive and consistent with the results obtained. Additionally, no evidence is found that the estimation results are affected by the level of income. The correlation coefficients found are high for both estimates for the Concentration high income and Boone low income samples with an average of .9.

The empirical results obtained in this study suggest that bank competition could be beneficial for economic growth. That is, as banking competition increases through the channel of efficiency and decreased concentration, this ultimately means increased economic growth. Therefore, it is suggested to implement measures that restrict the concentration of funds in a small number of banking institutions, as well as measures that encourage competition in the banking sector through policies that strengthen efficiency in the sector. On the other hand, a limitation of this analysis is that no control variables are incorporated. The findings suggest an important question: what would be the effect of competition in the banking sector on the stability of the sector in the long run?

References

Abdullah, S.M., Siddiqua, S. & Huque, R. (2017). Is health care a necessary or luxury product for Asian countries? An answer using panel approach. Health Economics Review. 7, 4 https://doi.org/10.1186/s13561-017-0144-8

Adu-Asare Idun, A., & Aboagye, A. (2014). Bank competition, financial innovations and economic growth in Ghana. African Journal of Economic and Management Studies, 5(1), 30–51. https://doi.org/10.1108/ajems-09-2012-0057

Ajisafe, R. A., & Ajide, F. M. (2014). Bank competition and economic growth: Evidence from Nigeria. Journal of Emerging Trends in Economics and Management Sciences, 5(5), 419-425. https://hdl.handle.net/10520/EJC163080

Banya, R. M., & Biekpe, N. (2017). Bank competition and economic growth. Journal of Economic Studies, 44(2), 245–265. https://doi.org/10.1108/jes-09-2015-0169

Bonaccorsi Di Patti, E. and Dell'Ariccia, G. (2004) Bank Competition and Firm Creation. Journal of Money, Credit, and Banking, 36, 225-251. https://doi.org/10.1353/mcb.2004.0011

Caggiano, G., & Calice, P. (2016). Bank Competition, Financial Dependence, and Economic Growth in the Gulf Cooperation Council. Policy Research Working Papers. https://doi.org/10.1596/1813-9450-7687

Cetorelli, N., & Gambera, M. (2001). Banking Market Structure, Financial Dependence and Growth: International Evidence from Industry Data. The Journal of Finance, 56(2), 617–648. https://doi.org/10.1111/0022-1082.00339

Coccorese, P. (2017). Banking competition and economic growth. Handbook of Competition in Banking and Finance, 230–263. https://doi.org/10.4337/9781785363306.00020

Choi, I. (2001). Unit root tests for panel data. Journal of International Money and Finance, 20(2), 249–272. https://doi.org/10.1016/s0261-5606(00)00048-6

Dayé, M., Houssa, R., & Reding, P. (2016). Improving MSMEs access to external financing in Low Income Countries: Is there a role for Development Cooperation? Reflets et Perspectives de La Vie Économique, Tome LV(1), 9–28. https://doi.org/10.3917/rpve.551.0009

Dell'Ariccia, G., & Marquez, R. (2004). Information and bank credit allocation. Journal of Financial Economics, 72(1), 185–214. https://doi.org/10.1016/s0304-405x(03)00210-1

de Guevara, J. F. & Maudos, J. (2017). Competition in the European banking markets in the aftermath of the financial crisis. Handbook of Competition in Banking and Finance, 118–138. https://doi.org/10.4337/9781785363306.00014 de Guevara J. F. & Maudos, J. (2007). Banking competition, financial dependence and economic growth. In Bank of Finland Conference Proceedings Financial Markets, Innovation and Growth.

Diallo, B., & Koch, W. (2018). Bank Concentration and Schumpeterian Growth: Theory and International Evidence. The Review of Economics and Statistics, 100(3), 489–501. https://doi.org/10.1162/rest_a_00679

Fohlin, C., & Jaremski, M. (2020). U.S. banking concentration, 1820–2019. Economics Letters, 190, 109104. https://doi.org/10.1016/j.econlet.2020.109104

Jayakumar, M., Pradhan, R. P., Dash, S., Maradana, R. P., & Gaurav, K. (2018). Banking competition, banking stability, and economic growth: Are feedback effects at work? Journal of Economics and Business, 96, 15–41. https://doi.org/10.1016/j.jeconbus.2017.12.004

Kao, C. D., & Chiang, M.-H. (1997). On the Estimation and Inference of a Cointegrated Regression in Panel Data. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2379

Levin, A., Lin, C.-F., & James Chu, C.-S. (2002). Unit root tests in panel data: asymptotic and finitesample properties. Journal of Econometrics, 108(1), 1–24. https://doi.org/10.1016/s0304-4076(01)00098-7

Lijesen, M. G., Nijkamp, P., & Rietveld, P. (2002). Measuring competition in civil aviation. Journal of Air Transport Management, 8(3), 189–197. https://doi.org/10.1016/s0969-6997(01)00048-5

Mark, N. C., & Sul, D. (2003). Cointegration Vector Estimation by Panel DOLS and Long-run Money Demand. Oxford Bulletin of Economics and Statistics, 65(5), 655–680. https://doi.org/10.1111/j.1468-0084.2003.00066.x

Mitchener, K. J., & Wheelock, D. C. (2013). Does the structure of banking markets affect economic growth? Evidence from U.S. state banking markets. Explorations in Economic History, 50(2), 161–178. https://doi.org/10.3386/w15710

Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. Nonstationary Panels, Panel Cointegration, and Dynamic Panels, 93–130. https://doi.org/10.1016/s0731-9053(00)15004-2

Pedroni, P. (2001). Purchasing Power Parity Tests in Cointegrated Panels. Review of Economics and Statistics, 83(4), 727–731. https://doi.org/10.1162/003465301753237803

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics, 22(2), 265–312. https://doi.org/10.1002/jae.951

Petersen, M. A., & Rajan, R. G. (1995). The Effect of Credit Market Competition on Lending Relationships. The Quarterly Journal of Economics, 110(2), 407–443. https://doi.org/10.2307/2118445

Phillips, P. C. B., & Hansen, B. E. (1990). Statistical Inference in Instrumental Variables Regression with I(1) Processes. The Review of Economic Studies, 57(1), 99. https://doi.org/10.2307/2297545

Rakshit, B., & Bardhan, S. (2019). Does bank competition promote economic growth? Empirical evidence from selected South Asian countries. South Asian Journal of Business Studies, 8(2), 201–223. https://doi.org/10.1108/SAJBS-07-2018-0079

Saikkonen, P. (1992). Estimation and Testing of Cointegrated Systems by an Autoregressive Approximation. Econometric Theory, 8(01), 1–27. https://doi.org/10.1017/S0266466600010720

Schaeck, K., & Cihák, M. (2013). Competition, Efficiency, and Stability in Banking. Financial Management, 43(1), 215–241. https://doi.org/10.1111/fima.12010

Stock, J. H., & Watson, M. W. (1993). A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems. Econometrica, 61(4), 783. https://doi.org/10.2307/2951763

Triki, T., & Gajigo, O. (2014). Credit Bureaus and Registries and Access to Finance: New Evidence from 42 African Countries. Journal of African Development, 16(2), 73–101. https://doi.org/10.5325/jafrideve.16.2.0073

Vural, G. (2020). Renewable and non-renewable energy-growth nexus: A panel data application for the selected Sub-Saharan African countries. Resources Policy, 65, 101568. https://doi.org/10.1016/j.resourpol.2019.101568

Appendix

Table A1. Countries shows High Income Boone (46 countries)

Austria, Bahamas, Bahréin, Barbados, Bélgica, Canadá, Chile, Croacia, Chipre, República Checa, Dinamarca, Estonia, Finlandia, Francia, Alemania, Hong Kong, Hungría, Irlanda, Israel, Italia, Japón, Kuwait, Letonia, Lituania, Luxemburgo, Macao, Malta, Países Bajos, Noruega, Omán, Panamá, Polonia, Portugal, Qatar, Arabia Saudita, Singapur, República Eslovaca, Eslovenia, España, Suecia, Suiza, Trinidad y Tobago, Emiratos Árabes Unidos, Reino Unido, Estados Unidos y Uruguay

Table A2. Countries sample Boone median income (58 countries)

Algeria, Angola, Argentina, Armenia, Azerbaiyán, Bangladesh, Bielorrusia, Belice, Bolivia, Bosnia y Herzegovina, Brasil, Bulgaria, Camboya, Camerún, China, Colombia, Costa Rica, Costa de Marfil, República Dominicana, Ecuador, Egipto, El Salvador, Georgia, Guatemala, Honduras, India, Indonesia, Jordán, Kazajistán, Kenia, Líbano, Libia, Mauritania, Mauricio, México, Moldavia, Marruecos, Nicaragua, Nigeria, Macedonia del Norte, Pakistán, Paraguay, Perú, Rumania, Rusia, Senegal, Serbia, Sudáfrica, Sri Lanka, Sudan, Tailandia, Túnez, Turquía, Ucrania, Uzbekistán, Venezuela, Vietnam y Zambia

Table A3. Countries sample Low Income Boone (8 countries)

Benín, Burkina Faso, Burundi, Etiopia, Malawi, Malí, Nepal y Uganda

Table A4. Countries sample High income Lerner (40 countries)

Australia, Bahamas, Bahréin, Bélgica, Canadá, Chile, Croacia, Chipre, República Checa, Dinamarca, Francia, Alemania, Hong Kong, Hungría, Israel, Italia, Japón, Letonia, Lituania, Luxemburgo, Macao, Malta, Países Bajos, Noruega, Omán, Panamá, Polonia, Portugal, Arabia Saudita, Singapur, República Eslovaca, Eslovenia, España, Suecia, Suiza, Trinidad y Tobago, Emiratos Árabes Unidos, Reino Unido, Estados Unidos y Uruguay

Table A5. Countries sample Average income Lerner (42 countries)

Argentina, Armenia, Azerbaiyán, Bangladesh, Bielorrusia, Bolivia, Brasil, China, Colombia, Costa Rica, Costa de Marfil, República Dominicana, Ecuador, El Salvador, Georgia, Honduras, India, Indonesia, Jordán, Kazajistán, Kenia, Líbano, Malasia, Mauricio, Marruecos, Nigeria, Macedonia del Norte, Pakistán, Paraguay, Perú, Rumania, Rusia, Senegal, Sudáfrica, Tailandia, Túnez, Turquía, Ucrania, Venezuela, Vietnam y Zambia

Table A6. Countries sample Low income Lerner (4 countries)

Benín, Burkina Faso, Burundi y Etiopia

http://dx.doi.org/10.22201/fca.24488410e.2022.3245

Table A7. Countries sample High Income Concentration (48 countries)

Australia, Austria, Bahamas, Bahréin, Barbados, Bélgica, Canadá, Chile, Croacia, Chipre, República Checa, Dinamarca, Estonia, Finlandia, Francia, Alemania, Grecia, Hong Kong, Hungría, Irlanda, Israel, Italia, Japón, Kuwait, Letonia, Lituania, Luxemburgo, Macao, Malta, Países Bajos, Noruega, Omán, Panamá, Polonia, Portugal, Qatar, Arabia Saudita, Singapur, República Eslovaca, Eslovenia, España, Suecia, Suiza, Trinidad y Tobago, Emiratos Árabes Unidos, Reino Unido, Estados Unidos y Uruguay.

Table A8. Countries Sample Median Income Concentration (56 countries)

Algeria, Angola, Argentina, Armenia, Azerbaiyán, Bangladesh, Bielorrusia, Bolivia, Bosnia y Herzegovina, Botsuana, Brasil, Bulgaria, Camerún, China, Colombia, Costa Rica, Costa de Marfil, República Dominicana, Ecuador, Egipto, El Salvador, Georgia, Guatemala, Honduras, India, Indonesia, Jordán, Kazajistán, Kenia, Líbano, Libia, Malasia, Mauricio, México, Moldavia, Marruecos, Nicaragua, Nigeria, Macedonia del Norte, Pakistán, Paraguay, Perú, Rumania, Rusia, Senegal, Serbia, Sudáfrica, Sri Lanka, Tailandia, Túnez, Turquía, Ucrania, Uzbekistán, Venezuela, Vietnam y Zambia

Table A9. Countries Sample Low Income Concentration (6 countries)

Benín, Burkina Faso, Burundi, Malawi, Nepal y Uganda