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The Impact of Financial Inclusion on Income Inequality

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Abstract

All around the world, the value of an inclusive financial system is prioritized. Since most of the Middle East and North Africa (MENA) region's governments lacked sufficient formal financial services and the majority of their populations lacked access to conventional bank accounts, the issue of financial exclusion became increasingly important. Financial inclusion benefits not only individuals and families but also entire communities as a whole and can stimulate the economy. This study's objective is to evaluate the impact of financial inclusion on MENA region's income inequality. The aim of this study is to investigate the impact of financial inclusion on the income inequality of MENA region countries. To achieve this aim, a three-dimension Financial Inclusion Index (FII) was created using Principal Component Analysis (PCA) to measure each country's level of financial inclusion. These dimensions are access, usage, and quality of financial services. Data was collected from 18 MENA (Middle East and North Africa) region countries using a sample period from 2004 to 2019. Based on a 2-step Generalized Method of Moments (GMM) system, the results showed that an increase in the level of financial inclusion leads to the decrease of MENA region countries' income inequality.

Keywords

Financial Inclusion Index, MENA Region Countries, Income Inequality, Principal Component Analysis, System Generalized Method of Moments

1. Introduction

Financial inclusion has been broadly recognized as a critical tool in reducing poverty and achieving inclusive economic growth, where greater access to financial services enables the marginalized groups to step out of poverty and reduces the inequality in the society. It not only benefits individuals, but collectively it develops the entire economy and accelerates economic growth.

An inclusive financial system has both micro and macro benefits. On a micro-scale, families are able to organize their income better, while having access to microfinance and credits permits them to plan their expenses and pay for an education plan, which offers them an opportunity to have a better future. Also, a nation can develop an entrepreneurial spirit through credits to allow people to set up small businesses, reflecting positively in the national economic output (Empresariales et al., 2013).

Moreover, financial inclusion has numerous direct benefits to poor individuals using savings or loans to smooth consumption, absorb shocks as health issues, or make investments in durable goods, school fees, or home improvements. Also, insurance can help the poor manage their financial risks (Collins et al., 2009).

On a macro level, participation in the formal financial system allows governments to better track money, resulting in easier tax collection and more funds available for investment. Furthermore, formal financial systems can detect and prevent money laundering; as a result, an inclusive financial system can reduce other forms of organized crime, such as financing terrorism and corruption. In the long run, it will help countries become more developed by establishing a financial system that is compliant with international standards such as VISA and MasterCard (Empresariales et al., 2013).

The aim of this paper is to address the issue of financial inclusion in different countries, specifically in the MENA region countries by constructing a multidimensional FII. Furthermore, this study aims to assess the impact of financial inclusion on income inequality in MENA region countries.

The contribution of this study is three-fold. First, using a two-step system GMM, this study provides a FII based on dynamic panel data analysis. This index was created using data spanning 16 years; from 2004 to 2019, offering a measure of variations of financial inclusion in 18 MENA region countries. Second, the current study provides insights into how increasing financial inclusion in MENA region countries may result in change in their income inequality level. Finally, the outcome of this study is useful both for policymakers and academics. Policymakers of MENA region countries may use the current study's findings to apply the suitable policies of financial inclusion. Academics may benefit from the current study by using a valid proxy for hypothesis testing purposes.

2. Literature Review

Based on previous studies, this section presents alternative definitions of financial inclusion and considers how an increase in financial inclusion may affect the income inequality.

2.1. Financial Inclusion

"Financial inclusion has the potential to improve the financial condition and level of living of the society's most disadvantaged members," writes (Khan, 2012). Khan also said that having access to basic banking services will boost economic activity and job prospects. This, however, has a multiplier impact on the economy since it leads to better disposable income for rural families, which leads to increased savings and a stronger deposit base for banks and other financial institutions. An inclusive financial system helps both the macro and micro levels. On a micro level, families are better able to arrange their finances, and having access to loans and microfinance helps them to plan their costs and pay for an educational plan, giving them the potential for a better future.

Mahendra Dev (2006) defined financial inclusion as "the availability of banking services at a reasonable rate to the major proportion of the vulnerable and low-income populations". He noted that, in addition to lending, financial inclusion provides a wide variety of services such as savings, insurance, payments, and remittance facilities provided by formal financial institutions.

Zins & Weill (2016) view financial inclusion as the fact that a person owns an account at a formal financial institution. Such an account allows the person to either save or borrow money formally, to contract insurance or to use payment services.

Financial inclusion is also defined by the Committee on Financial Inclusion chaired by (Rangarajan, 2008) as the process of ensuring access to financial services and timely adequate credit where needed by vulnerable groups such as weaker sections and low-income groups at an affordable cost.

Kim (2015) contends that people are excluded from formal financial services as a result of ineligibility, non-availability, financial illiteracy and non-affordability. This arises due to challenges with access, marketing, prices or voluntary exclusion in response to negative experiences or perception.

The provision of banking services to a significant portion of society is referred to as financial inclusion. It aids in the elimination of subsidy and welfare leakages, improves saving, enhances credit availability, and decreases poverty (Ellis et al., 2010). This increases money circulation, which raises investment and purchasing power parity while cutting inflation. Extending financial inclusion has also been shown to ensure monetary stability, minimize the cost of cash management, and safeguard the local currency's strength (Mbutor, 2013). Many definitions of financial inclusion have been proposed in prior research, with a similar focus on affordable access to a wide range of financial services (Bhaskar, 2013).

2.2. Financial Inclusion and Income Inequality

The primary purpose of financial inclusion is to give "unbanked" individuals access to formal financial services, allowing them to improve their standard of living and contribute to economic growth and development. However, the real impact of financial inclusion on income inequality is unknown. Financial inclusion, according to Beck et al. (2007), has a major influence on reducing poverty and income inequality. Townsend & Ueda (2006) found a transitional non-linear relationship between financial inclusion, shifting inequality, and economic progress. Several models show that the relationship between income inequality and financial inclusion is inverse, with income inequality influencing financial inclusion rather than the other way around. Despite the fact that the theoretical foundations of the relationship between financial inclusion and income inequality remain unsettled, empirical data shows a significant and meaningful association between the two.

In addition, Giné & Townsend (2004) discovered that the effect of financial inclusion on income inequality is achieved through including a bigger proportion of the population in productive activities in the economy and better salaries rather than just providing credit to the lower income. Moreover, Cyn-Young Park & Rogelio V. Mercado, (2015) found out that financial inclusion considerably reduces income disparity and poverty in developing Asia.

Omar & Inaba (2020) assessed the role of both dimensions of financial development (size of the financial sector and financial inclusion) in reducing income inequality. They found that financial inclusion contributed to reducing income inequality when the regression was controlled for key relevant factors, especially economic development and fiscal policy.

Financial inclusion can lift the financial condition and standard of living of poor and reduce income inequality (Beck et al., 2007).

Townsend & Ueda (2006) confirmed a transient non-linear relationship between financial inclusion with changing inequality and economic growth.

Claessens & Perotti (2007) in their study revealed that political exclusion creates unequal access to finance and eventually disproportionate opportunities which can reinforce income inequality.

C. Park & Mercado (2018a) assessed the cross-country impact of financial inclusion on poverty and income inequality across country income groups by introducing a new financial inclusion index for 151 economies, using principal component analysis and a cross-sectional approach. The results indicate that higher financial inclusion significantly co-varies with higher economic growth and lower poverty rates, but only for high and middle-high-income economies, not those that are middle-low and low-income. However, they did not find significant effect of financial inclusion on income inequality in any income group.

Cyn-Young Park & Rogelio V. Mercado (2015) found empirical evidence of a negative relationship between financial inclusion, poverty, and income inequality.

3. Data and Methodology

3.1. Data

The present study focuses on constructing a multidimensional FII following Cámara & Tuesta (2014); Park & Mercado (2018a) using PCA and seeks to evaluate the financial inclusion state across the MENA region countries, for the period from 2004 to 2019. Then measure the impact of financial inclusion on income inequality in the MENA region countries using a quantitative approach.

Sample

The population of this study is all the MENA region countries. According to the World Bank 2019 classification there are 19 countries in the MENA region. The intended sample size is equal to the population. Census implies complete enumeration of the study objects. After collecting the data for the 19 MENA region countries, one country—Bahrain—was removed due to the unavailability of data therefore the sample size used in this study is 18 countries as shown in **Table 1** below.

The type of data collected determines the research instruments that can be applied to analyze data. This study is based on quantitative research methods using secondary data. Secondary data do not introduce ethical issues, are more accessible, more cost-effective when compared to primary data. The data used in this study is time series and cross-sectional as data for all variables are collected for 18 countries annually for 16 years from 2004 to 2019.

3.2. Methodology

The overall aim of this study is to assess the impact of financial inclusion on income inequality in the MENA region countries. This study uses quantitative analytical techniques and secondary sources to address the critical research question.

Prior to assessing the impact of financial inclusion on income inequality, first the level of financial inclusion needs to be identified. To measure the level of accessibility of financial services in a country this step has to be taken first identifying the indicators and determining the level of financial inclusion. In order for the governments to set the polices and actions to increase the access and usage levels of financial services the country needs, reliable information about the level of the current financial inclusion has to be occurred.

Table 1. Sample of the study.

#	Countries		
1	Algeria	10	Morocco
2	Djibouti	11	Oman
3	Egypt	12	Qatar
4	Iran	13	Saudi Arabia
5	Iraq	14	Syria
6	Jordan	15	Tunisia
7	Kuwait	16	United Arab Emirates
8	Lebanon	17	West Bank and Gaza
9	Libya	18	Yemen

Source: prepared by the author based on data from the World Bank.

This section is composed of 3 main subsections. The first subsection describes in detail the process of constructing a FII. The specification of the model used to assess the impact of financial inclusion (using the FII) on income inequality is explained in subsection 3.2.2, while the empirical methods used explained in subsection 3.2.3.

Developing Financial Inclusion Index

Two approaches have been used alternatively in the literature, when constructing a composite index for measuring financial inclusion, parametric and non-parametric approach. The parametric approach where the weights are determined and assigned endogenously through the co-variation between the indicators on each dimension of the structure (Cámara & Tuesta, 2014; Le et al., 2019; Park & Mercado, 2018a; Sha'ban et al., 2020), while the non-parametric approach where the weights for the components of the FII are assigned exogenously, based on researchers' intuition (Chakravarty & Pal, 2013; Sarma, 2008). There is evidence that indices are sensitive to allocating weights subjectively since a minor change in weights may change the results dramatically (Lockwood, 2004); consequently, this study uses a parametric analysis when constructing the FII.

PCA and CFA are the two parametric analyses generally used for indexing. Preferring PCA is as an indexing strategy over CFA because it is not essential to make assumptions on the raw data, such as selecting the underlying number of common factors (Steiger, 1979), The applicability of this method lies in the fact that it reduces a fairly large number of variables into a smaller set of uncorrelated factors, it uses ideal weight to avoid the of researcher's bias. PCA is a statistical process that converts a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables using an orthogonal transformation.

When constructing the FII, all indicators were classified into three dimensions: access, usage, and quality of financial services. Each dimension required the creation of a sub-index that consists of many components that belong to this dimension's characteristics. The creation of sub-indices provides two benefits. First, each sub-index reflects a different element. Therefore, having a separate sub-index for each element is useful for policy decisions related to individual elements. Second, since sub-indices consist of indicators that are highly correlated, it is more feasible to calculate each sub-index separately and then calculate the overall FII using the sum of the three sub-indices.

In other words, the three sub-indices that characterize financial inclusion are estimated in the first stage: access, usage of, and quality. The dimension weights and overall financial inclusion index are computed in the second step by employing the dimensions as explanatory variables. Following El Bourainy et al. (2021) point of view, as an index technique, the two-stage PCA method is used to assess the extent of financial inclusion. This subsection focuses on the derivation of two-stage principal component indices. The calculation of the index involves the following steps:

Step 1: Normalization of Values of Indicators

Throughout country-specific values of the different indicators of financial inclusion there are significant differences. So as to guarantee enhanced comparison of these data, each indicator has been "normalized" using the UNDP goalpost method as used for measuring the initial international HDI as follows in Equation (1):

$$X_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where the normalized indicator for country *i*, is the corresponding pre-normalization figure, and are the maximum and minimum values of the same indicator across all the countries. For all individual categories of indicators, the normalized indicator takes a value of 0 to reflect the lower end of the country's scale of financial inclusion, while 1 represents the upper end of the country's degree of inclusion, and which fluctuates between 0 and 1 for all other nations. PCA was used to generate the country-specific FII using the above-mentioned normalized statistics.

Step 2: First Stage PCA

The first stage of PCA aims to estimate the dimensions, that is, the three unobserved endogenous variables D_i^A, D_i^U and D_i^Q and the parameters in the following equations:

$$D_i^A = \gamma_1 \text{branch}_{popi} + \gamma_2 \text{ATM}_{popi} + \gamma_3 \text{branch}_{km^2 i} + \gamma_4 \text{ATM}_{km^2 i} + \mu_i \tag{2}$$

$$D_i^U = \alpha_1 \text{DP/ACC} + \upsilon_i \tag{3}$$

$$D_i^Q = \beta_1 \text{GC} + \varepsilon_i \tag{4}$$

where: γ, α, and β: are coefficients for the equations to be estimated, μ_i, υ_i, and ε_i are the error terms of the three equations, branch_{popi}: Number of commercial bank branches per 100,000 adults, ATM_{popi}: Number of ATMs per 100,000 adults, $\text{branch}_{km^2 i}$: Number of commercial bank branches per 1000 km^2, $\text{ATM}_{km^2 i}$: Number of ATMs per 1000 km^2, DP/ACC: Number of deposit accounts with commercial banks per 1000 adults, GC: Getting Credit.

Step 3: Second Stage PCA

Following El Bourainy et al. (2021) it is assumed that the FII can be expressed as a linear function as follows:

$$\text{FII}_i = w_1 D_1^A + w_2 D_2^U + w_3 D_3^Q + \varepsilon_i \tag{5}$$

where FII_i: Financial Inclusion Index, D_i^A, D_i^U, and D_i^Q capture the access, usage and quality dimensions of financial inclusion respectively, subscript *i* denotes the country and ε_i: Error Term.

According to Beck et al. (2007) several nations are rapidly growing access to accounts in every part of the world. Four nations, Iran, Kuwait, Saudi Arabia, and the United Arab Emirates, were on the verge of full inclusion, with over 80% of adults having accounts. Of fact, these countries had a rather high participation rate in 2011.

A more encouraging development is the increase in account ownership among some previously underserved MENA area countries. In the UAE, the percentage in 2011 was 60%, but by 2017, it had risen drastically to 88%. In Egypt, the number in 2011 was 10%, but by 2017 it had risen to 33%, owing in part to the government's conversion of pension payments to electronic form and promotion of digital payments. Iraq, the West Bank and Gaza, Morocco, Oman, Tunisia, and other low-inclusion nations are demonstrating similar trend of recent acceleration. The rise in the MENA Region is due to the recent adoption of mobile accounts in lesser infrastructural markets.

4. Empirical Modeling

Many tools have to be used for testing the data in a study. Firstly, a measurement model should be conducted for developing the FII, in which the validity and reliability are computed, and the model fit indices are used to test the fitness of the measurement model. After developing the FII, a descriptive analysis is used to describe the research variables of the model conducted in this research. Then, the regression assumptions are verified for model under study. The regression assumptions are Normality, Multicollinearity, Autocorrelation, Heteroscedasticity, and Endogeneity. Then Pearson Correlation is applied followed by unit root tests to check for the stationarity of the data. Furthermore, co integration tests, namely; Pedroni test is used to check for the presence of long-term co integration between the dependent and independent variables of the model.

4.1. Descriptive Statistics

Before starting the regression analysis, summary of the statistics is performed to show general data properties. Descriptive statistics are simply the numerical procedures or graphical techniques used to organize and describe the characteristics or factors of a given sample (Fisher & Marshall, 2009). The mean, standard deviation, minimum and maximum values for each selected variable of the model were calculated.

4.2. Diagnostic Testing-Regression Assumptions

The normality assumption should be checked before doing both the correlation and regression analysis to define the tests utilized for the study. Furthermore, the assumptions of multicollinearity, heteroscedasticity, autocorrelation, and endogeneity must be validated in order to utilize the best regression approach.

The normality of the data is tested using the test developed by Alejo et al. (2015), who developed tests for skewness, kurtosis, and joint normality for panel data one-way error component model. As to check for the presence of multicollinearity problem in the data Pearson or Spearman correlation test will be used. Moreover, to test for the existence of the autocorrelation Wooldridge test will be used. Furthermore, the likelihood ratio test will be used to test the presence of heteroscedasticity. Finally, Durbin-Wu-Hausman (DWH) test or the augmented regression test for endogeneity detects endogenous regressors (predictor variables) in a regression model.

4.3. Correlation Analysis

A correlation matrix is a matrix that gives the correlations between all pairs of data sets. It provides a correlation coefficient between the variable under investigation and each other, allowing the relationship between these two variables to be evaluated. Correlations are used to find associations between two or more variables. The value of the correlation coefficient can fall between 0.00 (no correlation) and 1.00 (perfect correlation). Correlation analysis is performed to analyze structure and test direct relationships between independent and dependent variables (Cohen et al., 2000).

A normality test is first performed to distinguish between the use of Pearson and Spearman correlations. If the data are found to be normally distributed, Pearson's correlation is used. Otherwise, Spearman's correlation is used as it is a nonparametric test (Artusi et al., 2002).

4.4. Panel Regression Analysis

4.4.1. FGLS

To estimate the coefficients of the regression model, the FGLS method is applied, which allows for addressing the problem of autocorrelation heteroscedasticity and offers potential efficiency gains over OLS (Miller & Startz, 2019). Parks (1967) introduced FGLS, which fits panel-data linear models and produces unbiased and consistent parameter estimates in the presence of correlated and heteroscedastic error factors across the panels (Rosenfeld & Fornango, 2007). This allows estimation in the presence of within-panel autocorrelations and between-panel cross-sectional correlations and heteroskedasticity across groups. This method allows a robust estimation in the presence of autocorrelation within panels and heteroscedasticity across panels and the estimators are efficient asymptotically (Vogelsang, 2012). The below Equation (6) is used to apply the FGLS for the Model:

$$\mathrm{GINI}_{it} = \beta_0 + \beta_1 \mathrm{FII}_{it} + \beta_2 \mathrm{UNEMP}_{it} + \beta_3 \mathrm{SE}_{it} + \beta_4 \mathrm{PS}_{it} + \beta_5 \mathrm{CORP}_{it} + \lambda_i + \varphi_t + \varepsilon_{it} \quad (6)$$

4.4.2. Two-Steps System GMM

This study uses the GMM estimator reviewed by Arellano & Bover (1995) and thoroughly developed by Blundell & Bond (1998), In addition, the systematic GMM estimator provides consistent and efficient estimators, solves the endogeneity problem, and is more suitable for panel studies because it has fewer time points and a larger number of subjects (N > T), which is the case in this study where the number of countries is greater than the number of years.

Furthermore, the method combines regression in initial differences with regression in levels. To calculate the system estimator, the variables in differences are instrumented with the lags of their own levels, whilst the variables in levels are instrumented with the lags of their own differences (Al-Ammar et al., 2009). A two-step method in the case of heteroscedastic disturbances in large samples, Blundell & Bond (1998) recommend that GMM be applied in two phases rather than one. This is because the two-stage generates an ideal weighting matrix using the one-residuals stages. According to Roodman (2009), using time dummies strengthens the following assumption: "the autocorrelation test and the robust estimates of the coefficient standard errors presume no connection across individuals in the idiosyncratic disturbances." The following Equation (7) is used to investigate the impact of financial inclusion on the dependent variable; income inequality using the two-step system GMM estimator:

$$\begin{aligned} \mathrm{GINI}_{it} = {} & \beta_0 + \beta_1 \mathrm{GINI}_{i,t-1} + \beta_2 \mathrm{FII}_{it} + \beta_3 \mathrm{UNEMP}_{it} + \beta_4 \mathrm{SE}_{it} + \beta_5 \mathrm{PS}_{i} \\ & + \beta_6 \mathrm{CORP}_{it\ t} + \alpha_t + \varepsilon_{it} \end{aligned} \tag{7}$$

where $\mathrm{GINI}_{i,t-1}$ is the lagged income inequality, and α_t represents yearly dummies to control for time effects. It is important to include time effects to capture macro-economic factors that are beyond country control.

5. Empirical Results

The data analysis and interpretation of the results are covered in this section. It is divided into five sub sections. Developing the results of the FII using the PCA will be explained in sub section 5.1. Afterwards, the descriptive statistics findings are reported in sub-section 5.2, followed by the results of multiple diagnostic tests performed to detect model misspecification in sub-section 5.3. Subsection 5.4 examines the findings of the Dynamic two-step method GMM utilized to study the influence of financial inclusion on economic development in MENA area nations. The FGLS test findings are discussed in subsection 5.5.

5.1. Developing FI

This section is divided into three subsections, first to test the validity and reliability of the newly constructed FII. Following Cámara & Tuesta (2014); Park & Mercado (2018a); Le et al. (2019); Gualandri et al. (2019); El Bourainy et al. (2021), a two-step PCA method is used as an indexing strategy to assess the degree of financial inclusion, where the second and third sub sections 5.1.2 and 5.1.3 discuss the results of the first stage and second stage PCA.

5.1.1. Validity and Reliability

Table 2 below shows the KMO measure values for all the six indicators to identify the adequate indicators to be included to develop the FII.

Table 3 shows the KMO values for the remaining indicators to be added to the index after deleting one item. Due to a lack of item loading, ATMs with 100,000 adults were not included (Item Loading 0.49). Other goods were considered because their loading was more than 0.49. As a result, the FII will include a total of 5 indicators: three under the access dimension (NCBB 1000 km^2, NCBB 100,000 adults, ATMs 1000 km^2 and ATMs 100,000 adults), one under the usage dimension (Outstanding deposits under commercial banks% of GDP), and one under the quality dimension (Getting credit total score).

Table 4 shows that the Cronbach's alpha is greater than 0.7 implying that the data under study have adequate validity and reliability after deleting the mentioned items.

Table 5 presents the descriptive statistics about the indicators used to measure FII. As mentioned earlier, data for financial inclusion indicators were gathered for 18 MENA region countries for a period of 16 years resulting in 288 observations for each indicator. The maximum number of bank branches per 1000 Km^2 is 110, while the minimum is almost 0. The maximum number of bank branches per 100,000 adults was 32 branches, while the minimum is almost 1 branch. As for the ATMs, the maximum number of ATMs per 1000 Km^2 was around 195 ATMs, while the minimum was almost 0 ATMs.

Table 2. KMO Values for all indicators.

Variable	KMO
NCBB 1000 KM^2	0.5104
NCBB 100,000 Adults	0.5854
ATMs 1000 KM^2	0.5442
ATMs 100,000 Adults	0.4607
Outstanding deposits under commercial banks % of GDP	0.7907
Getting Credit total score	0.7494
Overall	**0.5729**

Source calculated by the author on STATA 16.

Table 3. KMO Values for the final indicators included in the index.

Variable	KMO
NCBB 1000 KM^2	0.6314
NCBB 100,000 Adults	0.6343
ATMs 1000 KM^2	0.6306
Outstanding deposits under commercial banks % of GDP	0.8183
Getting Credit total score	0.5051
Overall	**0.6452**

Source calculated by the author on E-views.

Table 4. Scale reliability coefficient: Cronbach's alpha.

Average interitem covariance	348.1601
NNNumbers of items in the scale	5
Scale reliability coefficient	0.7217

Source calculated by the author on E-views.

Table 5. Descriptive statistics for financial inclusion indicators.

Variable	Observation	Mean	Standard Deviation	Min	Max
NCBB 1000 KM^2	288	13.435	23.241	0.198	110.362
NCBB 100,000 Km^2	288	12.284	7.854	1.42	32.307
ATMs 1000 Km^2	288	27.416	42.17	0	195.797
Outstanding deposits under commercial banks% of GDP	288	70.248	52.009	9.058	250.727
Getting credit total score	288	4.903	3.412	0	16

Source calculated by the author on STATA 16.

5.1.2. First Stage PCA

The PCA approach is used to determine the eigenvalue of the access sub-index and estimate the latent variable: access (D_i^A), as shown in **Table 6**. The component with the highest eigenvalue, among other things, has higher standardized variance, and an eigenvalue greater than 1 is considered for the analysis (Nguyen, 2021). The first-stage PCA findings are shown in **Table 6**. The eigenvalues of the major components for the access dimension, in descending order, are: 2.16; 0.7; and 0.13. Except for the first main component, none of the others have an eigenvalue larger than 1. As a result, just the first component is analyzed, and the access dimension is approximated using the weights assigned to the first main component.

The extracted weights for each of the three indicators are shown in **Table 7**. As a result, the weights given to the first component of the access dimension are 0.6406 for the number of bank branches per 1000 Km^2; 0.4545 for the number of bank branches per 100,000 adults' indication; and 0.6188 for the number of ATMs per 1000 Km^2 indicator. Equation (8) is constructed for the access dimension by giving the above-extracted weights to Equation (2):

$$D_i^A = 0.6406\,\text{NCBBK} + 0.4545\,\text{NCBBA} + 0.6188\,\text{ATMs} \tag{8}$$

5.1.3. Second Stage PCA

In the second stage, the PCA approach is used to the three sub-indices (access, usage, and quality) to determine their weights in the overall FII using the same procedure outlined in the first stage. The findings of principal component estimates for the composite FII are shown in **Table 8**. The eigenvalues of the three major components are 1.85, 0.91, and 0.23 respectively. This demonstrates that only the first component has an eigenvalue larger than 1, hence it is used to calculate the weights of the primary components.

Similar to the method in the first phase, weights for the three dimensions are calculated. **Table 9** below shows the assigned weights to the access, usage and quality dimensions.

By assigning the above-extracted weights to Equation (5); the following Equation (9) is derived for the overall FII, respectively:

$$\text{FII}_i = 0.6864 D_1^A + 0.5923 D_2^U + 0.4219 D_3^Q + \varepsilon_i \tag{9}$$

Table 6. Principal components estimates for sub-indices.

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	2.16398	1.4595	0.7213	0.7213
Component 2	0.704487	0.57296	0.2348	0.9562
Component 3	0.131528	.	0.0438	1.0000

Source: calculated by the author using PCA on STATA 16.

Table 7. Principal components estimates for sub-indices.

Variable	Comp1	Comp2	Comp3	unexplained
NCBBK	0.6406	−0.2447	−0.7278	0
NCBBA	0.4545	0.8848	0.1026	0
ATMs	0.6188	−0.3966	0.6781	0

Source: calculated by the author using PCA on STATA 16.

Table 8. Principal Components Estimates for Sub-indices.

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	1.85476	0.944668	0.6183	0.6183
Component 2	0.910087	0.67493	0.3034	0.9216
Component 3	0.235157	.	0.0784	1.0000

Source: calculated by the author using PCA on STATA 16.

Table 9. Principal components (eigenvectors).

Variable	Comp1	Comp2	Comp3	Unexplained
Acess	0.6864	−0.0507	−07254	0
Usage	0.5923	−0.5397	0.5982	0
Quality	0.4219	0.8403	0.3404	0

Source: calculated by the author using PCA on STATA 16.

5.2. Descriptive Statistics Results

A preliminary step to the inferential analysis is the descriptive analysis presented in Table 10 below for all the variables used in this Model.

5.3. Diagnostic Testing

5.3.1. Normality

Table 11 below shows the joint test for normality on each component of the error term and their *p*-values. The joint test for normality in the remainder component (e) is found to be symmetric as the null hypothesis is accepted with a p-value 0.4665. Also, the joint test for normality in the country level component (u) is found to be symmetric since the *p*-value greater than 0.05, therefore the null hypothesis is accepted with a *p*-value 0.3423, indicating that the data in this model is symmetric and normally distributed.

Table 10. Descriptive statistics.

Variables	Observations	Mean	Standard Deviation	Min	Max
GINI Index	288	−0.477	0.657	−1	0.451
FII	287	0.266	0.216	0	1
UNEMP	288	9.788	5.687	0.11	26.26
EDU	288	100.256	13.502	42.139	128.46
PS	288	−0.744	1.114	−3.18	1.22
CORP	288	36.26	14.773	13	77

Source: calculated by the author on STATA 16.

Table 11. Panel data normality test results.

Tests	Observed Coefficient	Bootstrap Standard Error	Z	$P > \|z\|$	Normal Based [95% Conf. Interval]	
Skewness_e	0.002705	0.0259529	0.10	0.197	−0.0481618	0.0535718
Kurtosis_e	−0.0537893	0.0437138	−1.23	0.219	−0.1394667	0.0318882
Skewness_u	0.025474	0.0174117	1.46	0.143	−0.0086524	0.0596003
Kurtosis_u	−0.0007557	0.0124038	−0.06	0.951	−0.0250667	0.0235553
	Joint test for Normality on e				Joint test for Normality on u	
	chi^2 (2) Probability > chi^2			chi^2 (2)	Probability > chi^2	
	1.52 0.4665			2.14	0.3423	

Source: calculated by the author on STATA 16.

5.3.2. Autocorrelation

To test for the existence of autocorrelation, the Wooldridge test is applied. Results, as shown in the below Table 12, reveal that the probability value is insignificant and greater than 0.05. Therefore, the null hypothesis is accepted, and it can be concluded that this model doesn't have an autocorrelation problem.

5.3.3. Heteroscedasticity

To test for the existence of heteroscedasticity, the likelihood ratio test is used. The result shows that the probability value is significant (less than 0.05), and the null hypothesis is rejected, as shown in the below Table 13. Thus, the assumption of homoscedasticity is not fulfilled, and there is a heteroscedasticity problem in this model, revealing that variance of the error terms changes with the increase in income inequality.

5.3.4. Endogeneity

The Durbin-Wu-Hausman test computes a test of endogeneity for a panel regression estimated via instrumental variables. A rejection of the null hypothesis indicates that endogenous regressors' effects on the estimates are meaningful, and instrumental variables techniques are required. The result shows that the regressors of this model are endogenous as shown in the below Table 14.

Table 12. Results for wooldrige test.

F	31.052
Probability > F	0.000

Source calculated by the author on STATA 16.

Table 13. Results of likelihood ratio.

LR chi^2	308.25
Probability > chi^2	0.000

Source calculated by the author on STATA 16.

Table 14. Endogeneity test results.

Durbin-Wu-Hausman test of endogeneity	19.618
P-value	0.000

Source calculated by the author on STATA 16.

It is clear from the abovementioned diagnostic tests' results that there are no normality or autocorrelation problems in this model. On the other hand, this model suffers from heteroscedasticity and endogeneity problems.

5.3.5. Correlation Analysis

Table 15 shows the correlation matrix for the relationship between the variables of this Model. It can be observed that there is no strong correlation between the independent variables of this Model, indicating that this model does not suffer from multicollinearity problem. It was also found that there is a significant but weak negative relationship between FII and GINI. It can also be observed that there is a significant but weak negative relationship between GINI and PSI, GINI and CPI.

5.4. Two Steps System GMM

This section presents the panel regression results for this model to assess the impact of financial inclusion on income inequality in the MENA region countries. Autocorrelation and heteroscedasticity issues prevent the precise estimation of the standard errors, causing incorrect hypothesis tests about the significance of estimated coefficients. Moreover, the dependent variable of this model, income inequality, is endogenous over time. In other words, the income inequality for the period t is affected by the income inequality for the period t-1. To eliminate all these errors, overcome the endogeneity problem and enhance the robustness of the model, dynamic panel GMM estimation is therefore adopted to measure the impact of financial inclusion on income inequality in the MENA region countries from 2004 to 2019 (Table 16).

To check the robustness of the model a static technique is used which is the FGLS to examine the sensitivity of the findings to an alternative technique. Results of the FGLS technique are shown below in Table 17, and assure that FII has a significant negative impact on GINI in the MENA region countries supporting the results of the System GMM technique. When financial inclusion increases by 1-unit, income inequality decreases by 0.558.

Results of the FGLS technique are shown in Table 17 below, and assure that there is a significant positive relationship between UNEMP and the GINI supporting the results of the system GMM technique. While SE, PS and CORP have a weak negative significant impact on GINI.

Table 15. Pearson correlation matrix.

Variables	GINI	FII	UNEMP	PSI	CPI
GINI	1.000				
FII	0.125*	1.000			
UNEMP	0.130*	−0.301*	1.000		
SE	0.017	−0.052	−0.119*		
PSI	−0.150*	0.048	−0.081*	1.000	
CPI	−0.205	0.324*	−0.599*	0.250*	1.000

Source calculated by the author on STATA 16.

Table 16. Results of GMM.

Variables	GINI
Lag GINI	0.148***
	(0.0236)
FII	−0.558***
	(0.152)
UNEMP	0.0222**
	(0.00890)
SE	−0.00142
	(0.00389)
PS	−0.0967**
	(0.0409)
CORP	−0.00831*
	(0.00436)
Constant	−0.445
	(0.293)
Observations	269
Groups/Instruments	11
AR(2) test	0.156
Hansen test	0.622

Source calculated by the author on STATA 16. Note: Standard errors are in parentheses.

Table 17. Results of FGLS.

Variables	GINI
FII	−0.894***
	(0.148)
UNEMP	0.0213***
	(0.00789)
SE	−0.00151
	(0.00277)
PS	−0.0943***
	(0.0253)
CORP	−0.0114***
	(0.00283)
Constant	−0.520
	(0.335)
Observations	288
Groups/Instruments	11

Source calculated by the author on STATA 16. Note: Standard errors are in parentheses.

In summary, after composing the multidimensional FII using 3 dimensions; access, usage and quality, the FII was used to assess the impact of financial inclusion on income inequality in MENA region countries, using two step system GMM and FGLS. The results of both techniques reveal that financial inclusion has a negative impact on income inequality. In other words, an increase in the level of financial inclusion leads to the decrease of MENA region countries' income inequality.

6. Conclusion

As it is known that financial inclusion contributes to more equitable macroeconomic growth, reduces poverty, and promotes income equality in the MENA region countries by providing access to formal financial services, this study empirically examines the impact of financial inclusion on income inequality. Moreover, this study constructs a new composite financial inclusion index using access, usage, and quality dimension of financial inclusion.

This study developed a new multivariate FII for 18 MENA countries based on the models of Cámara and Tuesta (2014), Park and Mercado (2015), El Bourainy et al. (2021) which employ PCA-derived weights to integrate access, usage, and quality metrics using the FAS database. This index may be used to measure the level of financial inclusion in various countries and track their income inequality over time. Researchers may use this index to experimentally analyze the effect of financial inclusion on other macroeconomic variables such as inflation, economic growth, inequality, poverty, and unemployment rates. Furthermore, using dynamic panel estimates, this article examined the impact of financial inclusion on income inequality in the MENA region. According to estimates, an increase in financial inclusion leads to a decrease in income inequality.

Since income inequality is one of the challenges facing countries in the MENA region, governments and central banks should work hard and focus on increasing the level of financial inclusion, not only the availability of finance, but also the use of finance and degrees. Promoting financial inclusion in the future would enable countries in the MENA region to achieve an important milestone. Increasing the level of financial inclusion is necessary and urgent for sustained economic growth (Sharma, 2016; Sethi & Sethy, 2018), leading to the decreasing of income inequality and increasing the equality in countries.

Finally, countries should enhance the exchange of experiences between countries through international financial institutions such as AFIs and GPFIs. Such organizations need to work together to develop financial inclusion in MENA countries with low levels of financial inclusion. Information on financial inclusion indicators is still limited. Several aspects of financial inclusion are typically included in these dimensions (access, usage, quality).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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