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The Impact of Financial Inclusion on Economic Development

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ABSTRACT

The importance of an inclusive financial system is considered a priority all over the world. The importance of financial inclusion raised from the problem of financial exclusion were most of the Middle east and North Africa (MENA) region countries didn't have enough formal financial services and most of the population didn't have access to formal bank accounts. Financial inclusion not only helps individuals and families, but collectively it develops entire communities and can help drive economic development. The purpose of this study is to assess the effects of financial inclusion on economic development in the MENA region. The aim of this study is to investigate the impact of financial inclusion on the economic development 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 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 increase of MENA region countries' economic development.

Keywords: Financial Inclusion, MENA Region Countries, Economic Development, Principal Component Analysis, System Generalized Method of Moments

JEL Classifications: C33, E24, O11, O16

1. INTRODUCTION

This study attempts to complement knowledge in the literature on the concept of financial inclusion with insights on financial inclusion levels particularly in the MENA region. This is achieved by constructing a three-dimension FII. These three dimensions are access to, usage of, and quality of financial services.

The contribution of this study is three-fold. First, using a two-step GMM system, 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 economic development 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.

The rest of the study is organized as follows: The following section reviews the literature that examined the impact of financial inclusion on economic development. Section three explains the data and the methodology used. Section 4 presents and analyzes the empirical results. The main findings and the implications of the study are highlighted in the fifth section.

2. LITERATURE REVIEW

Some definitions of financial inclusion are presented in this section and examines how increasing financial inclusion can affect economic development in MENA countries based on previous studies.

2.1. Financial Inclusion

Financial inclusion, often referred to as the expansion of financial systems, financial services or financial products, so that adults have greater access to society. Statistics have illustrated that many nations have recorded to set financial inclusion implementation as a formal goal to support their economic growth and development (Sahay et al., 2015). It helps in widening the financial network in order to create an effective financial flow within a country's border. Inclusion is expected to increase people's opportunities, reduce poverty and increase economic development.

Čihák et al. (2016) described financial inclusion as the set of financial services that individuals and businesses tend to use, rather than describing it as the financial services they have access to. The use of "tendency" instead of "access" to describe financial inclusion is more reflective of the services' actual use and better captures the concept's various dimensions. Understanding financial inclusion and creating proxies to measure it offers implications for central banks to improve their management of financial services' accessibility (Mehrotra and Yetman, 2015).

2.2. Financial Inclusion and Economic Development

Financial inclusion, is commonly known as access to formal financial services for example credit secure savings and insurance. FI has been identified as a critical tool of economic development (Claessens and Perotti, 2007). The greater the access of firms and households to various banking services the stronger the positive impact on economic development (Sahay et al., 2015).

Raza et al. (2019) found that there is a positive association between financial inclusion and economic development. In their study, financial inclusion was represented by the number of bank accounts (per 1,000 adults) and the number of bank branches (per 100,000 people) and economic development was represented by the human development index (HDI).

A number of studies concluded that financial development and economic development are positively related (Abu-Bader and Abu-Qarn, 2008). Research by Beck et al. (2007) examined that an accessible well-developed financial system decreases information and transaction costs and affects savings rates, technological innovations, long run growth rates, and investment decisions.

In a later study by (Sahay et al., 2015), it was also found that financial inclusion increases economic development up to a point. Greater access of firms and households to various banking services led to higher growth and that sectors that depend on external finance grow more rapidly in countries with greater financial inclusion. However, the marginal benefits for growth decrease as both inclusion and depths increase and become low, or even negative, for some advanced economies.

3. DATA AND METHODOLOGY

3.1. Data

The present study focuses on constructing a multidimensional FII following Cámara and Tuesta, (2014); (Park and Mercado, 2018) 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 economic development in the MENA region countries using a quantitative approach.

3.1.1. 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 the 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 economic development in the MENA region countries. This study uses quantitative analytical techniques and secondary sources to address the critical research question. Quantitative research uses statistics and mathematics to report research findings.

3.2.1. Measuring financial inclusion index

Two approaches have been used alternatively in the literature, when constructing a composite index for measuring financial inclusion, the approaches are a parametric approach where the weights are determined and assigned endogenously through the co-variation between the indicators on each dimension of the structure (Cámara and Tuesta, 2014; Le et al., 2019; Park and Mercado, 2018; Sha'ban et al., 2020), and a non-parametric approach where the weights for the components of the FII are assigned exogenously, based on researchers' intuition (Chakravarty and 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 to, usage of, 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 Cámara and Tuesta, (2014) 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:

3.2.1.1. 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 goal-post method as used for measuring the initial international HDI as follows in equation (1):

$$X_i = \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \quad (1)$$

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.

3.2.1.2. 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:

$$D_i^A = \gamma_1 branch_{popi} + \gamma_2 ATM_{popi} + \gamma_3 branch_{km^2 i} + \gamma_4 ATM_{km^2 i} + \mu_i \quad (2)$$

$$D_i^U = \alpha_1\, DP/ACC + \upsilon_i \quad (3)$$

$$D_i^Q = \beta_1\, GC + \varepsilon_i \quad (4)$$

Where: $\gamma_,$ 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, $branch_{km^2 i}$: Number of commercial bank branches per 1,000 km², $ATM_{km^2 i}$: Number of ATMs per 1,000 km², DP/ACC: Number of deposit accounts with commercial banks per 1,000 adults, GC: Getting Credit.

3.2.1.3. Step 3: Second stage PCA

Following Cámara and Tuesta (2014), it is assumed that the FII can be expressed as a linear function as follows:

$$FII_i = w_1 D_1^A + w_2 D_2^U + w_3 D_3^Q + \varepsilon_i \quad (5)$$

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 Spearman 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 statistics are performed to show general data properties, listing the mean, standard deviation, minimum and maximum values for each selected variable of the model.

4.2. Diagnostic Testing-regression Assumptions

According to Chibba (2009) and Mindra et al. (2017), testing data for compliance with the statistical assumptions underpinning multivariate approaches is critical in order to ensure a successful analysis due to the following factors: (a) the complicated linkages that exist in a large number of variables; and (b) the overall complexity of the study and findings, which ensures model resilience.

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, 2013).

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 and Startz, 2019). (Parks, 2012) 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 and 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:

$$HDI_{it} = \beta_0+\beta_1 FII_{it}+\beta_2 LFPR_{it}+\beta_3 TO_{it}+\beta_4 INF_{it}+\lambda_i+\varphi_t+\varepsilon_{it} \qquad (6)$$

4.4.2. Two-steps system GMM

This study uses the GMM estimator reviewed by (Arellano and Bover, 1995) and thoroughly developed by (Richard and Bond, 1998), as well as the Windmeijer restricted sample-adjusted standard errors (2005). 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 and 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; economic development using the two-step system GMM estimator:

$$HDI_{it} = \beta_0+\beta_1 \mathrm{HDI}_{i,t-1}+\beta_2 \mathrm{FII}_{it}+\beta_3 \mathrm{LFPR}_{it}+\beta_4 \mathrm{TO}_{it}+\beta_5 \mathrm{INF}_{it}+\alpha_t+\varepsilon_{it} \qquad (7)$$

Where $\mathrm{HDI}_{i,\ t-1}$ is the lagged economic development, 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 AND DISCUSSION

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

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 & Gaza
9	Libya	18	Yemen

Source: Prepared by the author based on data from the World Bank 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 FII

This section is divided into three subsections, first to test the validity and reliability of the newly constructed FII. Following (Cámara and Tuesta, 2014; (Park and Mercado, 2018); Le et al., (2019); Gualandri et al., 2019), 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 5.2.2 and 5.2.3 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 1,000 km^2, NCBB 100,000 adults, ATMs 1,000 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 2: KMO values for all indicators

Variable	KMO
NCBB 1,000 km^2	0.5104
NCBB 100,000 adults	0.5854
ATMs 1,000 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 1,00 Km^2	0.6314
NCBB 100,000 adults	0.6343
ATMs 1,000 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
Number of items in the scale	5
Scale reliability coefficient	0.7217

Source: Calculated by the author on E-views

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

Table 5 above 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 1,000 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 1,000 Km^2 was around 195 ATMs, while the minimum was almost 0 ATMs.

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 >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 1,000 Km^2; 0.4545 for the number of bank branches per 100,000 adults' indication; and 0.6188 for the number of ATMs per 1,000 Km^2 indicator. Equation (8) is constructed for the access dimension by giving the above-extracted weights to Equation (2):

$$DiA = 0.6406\ NCBBK + 0.4545\ NCBBA + 0.6188\ ATMs \quad (8)$$

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

Table 5: Descriptive statistics for financial inclusion indicators

Variable	Observation	Mean	Standard deviation	Min	Max
NCBB 1,000 km^2	288	13.435	23.241	0.198	110.362
NCBB 100,000 adults	288	12.284	7.854	1.42	32.307
ATMs 1,000 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 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 1.40, 0.599, and 1.40, 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:

$$FII_i=0.6864D^1A+0.5923D^2U+0.4219D^3Q+\varepsilon_i \quad (9)$$

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 the model (HDI, FII, LFPR, TO and INF). The average economic development from 2004 to 2019 across the 18 MENA region countries is 70.6%. The maximum development rate was 89% in UAE in 2019. While income growth in 2019 is likely to be limited due to low oil prices and fee reductions, the loss may be offset by VAT revenue. Overall, the budget balance is forecast to revert to deficit in 2019, but to recover progressively over the medium term. Abu Dhabi recently offered ten billion dollars in bonds to pay the deficit, its first overseas sale since 2017. (World Bank Group, 2018). The lowest HDI, on the other hand, was 39.3% in Djibouti in 2004. According to the UNDP's human development index, it was 154th out of 177 nations in 2004 (12th in the group of 36 countries with low human development). Over two-fifths of the population is impoverished, with 83% living in rural regions.

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
Access	0.6864	−0.0507	−0.7254	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

Table 10: Descriptive statistics

Variables	Observations	Mean	Standard deviation	Min	Max
HDI	288	0.706	0.108	0.393	0.89
FII	287	0.266	0.216	0	1
LFPR	288	0.548	0.133	0.38	0.885
TO	288	0.929	0.472	0.253	3.48
INF	288	0.059	0.075	−0.101	0.532

Source: Calculated by the author on STATA 16. HDI: Human development index

5.3. Diagnostic Testing

5.3.1. Normality

The P-values for the joint test for normality on each component of the error term are shown in Table 11. With a P = 0.4767 accepting the null hypothesis, the joint test for normality in the residual component (e) is found to be symmetric. Furthermore, because the P-value for the joint test for normality at the nation level component (u) is >0.05, the null hypothesis with a P = 0.2001 is accepted, demonstrating that the data in this model is symmetric and normally distributed.

5.3.2. Autocorrelation

The Wooldridge test is used to detect whether or not autocorrelation exists. The results, as shown in Table 12, show that the probability value is significant and <0.05. As a result, the null hypothesis is rejected, and it is reasonable to conclude that this Model exhibits autocorrelation, which suggests that the error variables are interconnected.

5.3.3. Heteroscedasticity

To determine the presence of heteroscedasticity, the likelihood ratio test is performed. The probability value is significant (<0.05), as shown in Table 13, and the null hypothesis is rejected. As a result, the homoscedasticity requirement is broken, and this Model has a heteroscedasticity problem, indicating that the variance of the error components fluctuates as economic growth increases.

5.3.4. Endogeneity

Fifthly, 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.

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

5.3.5. Correlation analysis

According to the normality tests, data was found to be normally distributed. Therefore, the Pearson correlation was used to test

Table 11: Panel data normality test results

Tests	Observed coefficient	Bootstrap standard error	Z	P>|z|	Normal based [95% Conf. interval]	
Skewness_e	−0.0000296	0.0000314	−0.94	0.345	−0.0000912	0.0000319
Kurtosis_e	6.45e-06	8.39e-06	0.77	0.442	−1.00e-05	0.0000229
Skewness_u	−0.0001268	0.0000893	−1.42	0.155	−0.0003018	0.0000481
Kurtosis_u	−0.0000135	0.0000123	−1.10	0.274	−0.0000375	0.0000106
Joint test for normality one			Joint test for normality on u			
Chi² (2)		Probability >Chi2	Chi² (2)		Probability >Chi²	
1.48		0.4767	3.22		0.2001	

Source: Calculated by the author on STATA 16

Table 12: Results for wooldridge test

F	112.311
Probability > F	0.0000

Source: Calculated by the author on STATA 16

Table 13: Results of likelihood ratio test

LR Chi-square	8300.17
Probability >Chi-square	0.000

Source: Calculated by the author on STATA 16

Table 14: Endogeneity test results

Durbin-Wu-Hausman test of endogeneity	18366.23
P-value	0.000

Source: Calculated by the author on STATA 16

Table 15: Pearson correlation matrix

Variables	HDI	FI	LFPR	TO	INF
HDI	1.000				
FII	0.542*	1.000			
LFPR	0.470*	0.310*	1.000		
TO	−0.135*	−0.017	0.422*	1.000	
INF	−0.190*	−0.163*	−0.255*	−0.234*	1.0000

Source: Calculated by the author on STATA 16

the relationship between the research variables. Table 15 shows the correlation matrix for the relationship between the variables of this Model. It can be observed that there is a weak 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 positive relationship between FII and HDI. It can also be observed that there is a significant but weak positive relationship between HDI and LFPR. Moreover, there is a weak negative relationship between HDI and TO and INF.

5.4. Two Steps System GMM

This section presents the panel regression results for this Model to assess the impact of financial inclusion on economic development 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, economic development, is endogenous over time. In other words, the economic development for the period t is affected by the economic development 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 economic development in the MENA region countries from 2004 to 2019.

Table 16: Results of GMM

Variables	HDI
Lag HDI	0.834***
	(0.0465)
FII	0.0258***
	(0.0131)
LFPR	0.0743***
	(0.0157)
TO	−0.00916***
	(0.00465)
INF	−0.0166*
	(0.00946)
Constant	0.0799***
	(0.0275)
Observations	269
Groups/Instruments	11
AR (2) test	0.688
Hansen test	0.664

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

Table 17: Results of FGLS

Variables	HDI
FII	0.132***
	(0.0146)
LFPR	0.357***
	(0.0206)
TO	−0.0213*
	(0.0109)
INF	−0.00256
	(0.0313)
Constant	0.506***
	(0.0112)
Observations	288
Groups/instruments	11

Source: Calculated by the author on STATA 6. Note: Standard errors are in parentheses

Table 16 shows the system GMM results for this Model, which indicates that FI has a significant positive impact on HDI. As for the control variables, LFPR has a significant positive impact on HDI supporting the findings of (Shahid, 2014). While the variables TO and INF have significant negative impact on HDI supporting the findings of (Keho, 2017).

5.5. FGLS Results

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 in Table 17, and assure that there is a significant positive relationship between FII, LFPR and the HDI supporting the results of the system GMM technique. Meaning that when FII increases by 1unit HDI will increase by 0.132 units. While TO has a weak negative significant impact on HDI.

6. CONCLUSION

This study developed a new multivariate FII for 18 MENA countries based on the models of Cámara and Tuesta, (2014) and Park and Mercado, (2015), 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 growth 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 influence of financial inclusion on the economic development of nations in the MENA region. According to estimates, an increase in financial inclusion leads to an increase in economic development.

Since economic development 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 and Sethy, 2019), leading to economic development, increasing both financial inclusion and the economic development as mentioned in the previous studies (Elsherif, 2019).

In addition, as mentioned above, governments should enlighten the awareness of financial literacy because it is seen as a tool to expand financial inclusion, in other words, it is a main step to promote financial inclusion because it increases people's understanding it makes people seek access to financial services and products. Creation of an institution serving as a center for financial literacy, including; research, collaboration and development of financial education is recommended. Collaborating with policy makers, entrepreneurs and researchers in the field makes sense to strengthen and coordinate the exchange of information. The collaboration could increase the vitality of financial literacy and good practices in dealing with financial matters. Increasing the level of financial literacy in the country can also be achieved directly with the help of industry players and researchers through various methods, such as round tables, conferences, campaigns and financial education fairs. Mass media such as television commercials, radio broadcasts, and newspaper articles can also be used to emphasize financial literacy. In addition, representatives of banks and financial institutions can offer orientation sessions and marketing activities to increase knowledge of non-financial individuals and institutions.

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). Additionally, this study is limited.

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