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An Investigation into the Level of Financial Inclusion among Regional Blocs in Africa

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An Investigation into the Level of Financial Inclusion among Regional Blocs in Africa

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Abstract

The availability and equal opportunity to access and use financial services determine an inclusive financial system. This has been the core objective of many nations as it plays a crucial role in economic development. However, investigation concerning financial inclusion among emerging regional blocs have not really been carried out in the literature. There are opportunities for future research in that area because regional blocs will not only proffer solutions that will improve the economic condition of member countries but will also make unified financial policies that will enhance the level of inclusive finance among its member states. This paper contributes to literature by determining the level of financial inclusion among the eight regional blocs in Africa. Two stage robust principal component analysis was carried out on Findex and Financial Access Survey data to ascertain the three sub-indices of financial inclusion (access, usage and quality), as well as the financial inclusion index of the blocs over the period of 2011, 2014, and 2017. SADC, ECOWAS, COMESA and, CEN-SAD outperformed AMU, EAC, ECCAS and IGAD which have not improved beyond a low level of financial inclusion. Previous researchers have identified the whole African region as that which needs proper attention in terms of financial inclusion. This information would create awareness on the areas that need immediate attention. Future work should examine the demographic characteristics of the population that are financially inclusive against the ones that are not.

1 Introduction

1.1. Background to the study

The ability of individuals and businesses to have access to basic and affordable financial products and services that satisfy their needs, irrespective of their income level is regarded as financial inclusion or inclusive finance (Adegboye and Iweriebor, 2018; Zhang and Posso, 2019). Through financially inclusive systems, vulnerable people and households are encouraged to borrow, save, and make investment in education. This in turn enables them to develop their entrepreneurial ventures. Since inclusive finance aims to eliminate the barriers that hinder people from taking part in the financial sector, it is important to differentiate between inclusive and exclusive finance.

Financial exclusion has to do with the poor and disadvantaged social groups being unable or having to face challenges in accessing financial services (Zhang and Posso, 2019). While some are financially excluded as a result of barriers to access e.g. the disadvantaged or hard to reach populace which includes women or poor residents of the rural areas, others are excluded by choice (self-exclusion). The latter may occur due to cultural reasons, low level of

financial literacy, which may cause individuals to see themselves as unsuitable, or it could be as a result of their negative experience with financial services in the past (Ibrahim and Aliero, 2020).

Improved financial inclusion has been the core objective of many developing economies, as several research findings have verified its relevance to an economy (Ayoola *et al.*, 2019). International bodies, policymakers, apex banks, financial institutions, and governments have developed interest in inclusive finance as it is recognized as part of the major socioeconomic challenges on their agenda. This result from the acknowledgement that, it is perceived as a significant strategy used to attain the United Nation's Sustainable Development (UNSD) goals, it assists with improving the level of social inclusion in several societies, can aid the reduction of poverty levels to an ideal minimum and bring about some other socio-economic benefits (Ozili, 2020). It is expected of policy makers to understand the contributing factors to financial exclusion and investigate the mechanisms that could be adopted to tackle this phenomenon. On that account, measurement of financial inclusion is important as it would aid its understanding as well as help to identify chances of eliminating the barriers that might be hindering people from making use of financial services (Klapper and Singer, 2018).

The Global Findex database, introduced by the World Bank, and Financial Access Survey (FAS) data provided by International Monetary Fund have made it possible to respectively measure demand and supply side financial inclusion in a systemic way for adults around the world[1][2]. Demand side provides information about barriers and usage of financial inclusion, while supply side identifies access to financial inclusion[3].

Investigation concerning inclusive finance in emerging regional blocs have not really been carried out in the literature, and there are opportunities for future research in that area(Ozili, 2020). Regional blocs such as EU, ECOWAS, ASEAN, etc. will not only provide collaborative solutions that will enhance the economic wellbeing of citizens of member countries in the bloc but will also make unified financial policies that will help increase the access individuals in member countries of the regional bloc have to finance. In lieu of this, future research can make comparison between the level of financial inclusion among regional economic blocs (Ozili, 2020). Hence, this paper attempts to contribute to existing literature on financial inclusion by focusing on regional blocs. The main contribution to literature is to determine the level of financial inclusion among the eight regional blocs in Africa. This would assist in identifying the regions that needs immediate attention in terms of financial inclusion.

1.2. Research Question and Objectives

This study attempts to answer the following research question:

"To what extent are the regional blocs in Africa financially inclusive?"

[1] https://globalfindex.worldbank.org/
[2] http://datahelp.imf.org/knowledgebase/articles/882546-what-is-the-financial-access-survey-fas#:~:text=The%20Financial%20Access%20Survey%20(FAS)%2C%20launched%20in%202009%2C,and%20benchmark%20progress%20against%20peers.
[3] https://www.worldbank.org/en/topic/financialinclusion/brief/how-to-measure-financial-inclusion

The objectives are:

a. To rank Africa's regional economic blocs in terms of access, usage, and quality of financial inclusion over the period of 2011, 2014 and 2017.

b. To rank and compare the regional blocs in Africa based on their level of financial inclusion over the period of 2011, 2014 and 2017.

Implementation of this study lies on the application of robust principal component analysis to calculate the index of financial inclusion for the various regional blocs in Africa, as well as sub-indices of the dimensions of inclusive finance considered in this paper; access, usage and quality. The research seeks to utilize both Findex and FAS data for a comprehensive analysis but is limited by data unavailability and not all the regional blocs are fully represented.

The rest of the paper is structured as follows:

a. Section 2 discusses the state of literature which demonstrates the comparison of existing research.

b. Section 3, 4, and 5 describe the methodology, model specification, and implementation, respectively.

c. Evaluation of results, discussion and limitation are presented in section 6.

d. Section 7 contains the conclusion and proposed future research.

2 Related Work

2.1 Dimensions of Financial Inclusion

The definition of financial inclusion cuts across different dimensions such as, accessibility, quality, availability and usage of the financial system (Adalessossi and Kaya, 2015). (Deepti and Vaidhyasubramaniam, 2018) stated that, of all the several indicators of financial inclusion, penetration, availability, and usage of banking services are the most significant. For improved financial inclusivity in a nation, its financial system needs to penetrate more to have as many users as possible. The size of the banked population, which refers to the percentage of people with a formal account as well as those with mobile money account are used to measure the penetration of financial institutions' in an economy. Notwithstanding, in the absence of data related to the number of banked people, the amount of bank account deposits per 1000 adult population can be used to measure this dimension.

Availability of financial services have to do with the presence, proximity, and accessibility of financial institutions to enable easy access and frequent usage. In an inclusive financial system, banking services must be easily available to the users. As such, indicators of availability of financial services are the number of branches of commercial banks, micro finance institutions, regulated credit union and cooperative societies per 100,000 adults. In addition, the number of Automated Teller Machine (ATM) per 100,000 adults, ATMs per

1000 km2, number of PoS Terminals and mobile money agent outlet are indicators of this dimension (Ayoola *et al.*, 2019).
Usage being the third dimension shows the extent at which the financial services offered by the financial institutions are used. It has been discovered that in some countries where a high number of formal account is being recorded, not many make use of the financial services due to different reasons such as availability of banking outlets, demanding conditions attached to financial services, amongst others. Therefore, having a bank account is not an adequate measure of an inclusive financial system (Ayoola *et al.*, 2019). Thus, in estimating the usage dimension, two basic appropriate indicators have been noted in literature, they are: deposit and credit from commercial banks, micro finance institutions, credit union and cooperative societies (Deepti and Vaidhyasubramaniam, 2018).

While literatures such as (Deepti and Vaidhyasubramaniam, 2018; Ayoola *et al.*, 2019) had the same view and measured financial inclusion based on similar indicators for penetration, availability and usage, (Sethy, 2018; Sha'ban, Girardone and Sarkisyan, 2020) were of a different opinion. Although, the latter accepted the indicators identified to measure usage, reason being that usage was regarded as the reflection of the outreach of financial services to adults. In place of penetration, depth dimension was recognized, and availability remained the same but was referred to as access. The dimension called depth was defined as the actual usage of financial services and was captured by two indicators: bank deposits and domestic credit to private sector by banks, like usage indicators but they were scaled by GDP. Hence, usage, access and depth were considered the dimensions of financial inclusion in the paper. The former on the other hand, did not deviate from the indicators considered for penetration and availability but included savings, access to insurance, as well as banks risk to measure access and availability. Also, usage was measured with outstanding deposit with commercial banks as a percentage of GDP .

Contrary to the indicators that make up access dimension as established by the literatures above, (Goel and Sharma, 2017) identified number of life insurance offices. Unlike studies which stated three dimensions of financial inclusion, (Jukan and Softic, 2016; Lyons and Kass-Hanna, 2019) recognized only one, the usage dimension. Although, both literatures defined financial inclusiveness in term of account ownership, savings and borrowing, but (Jukan and Softic, 2016) went further by adding the usage of debit card and mobile account.

(Nuzzo and Piermattei, 2020) believed financial inclusion is dependent on individual's ability to access savings rather than credit. In that regard, all variables associated to credit were considered misrepresentation of the dimensions in which financial inclusion should be properly represented. This counters (Deepti and Vaidhyasubramaniam, 2018) proposition of the volume of credit being an appropriate measure of usage dimension.

(Cámara and Tuesta, 2014) postulated that concentrating only on usage and access, results to constrained estimation of financial inclusion because they do not contain information about the quality of the financial inclusion process or the amount of people financially excluded. Data concerning the apparent reasons people do not use formal financial services contributes significant information to the degree of inclusiveness of a financial system. The barriers considered by unbanked populace provide information about what prevents them from making use of formal financial services. This thus offers an extra angle to which the degree of financial inclusion can be assessed. Barrier as a dimension was measured in the literature with only the information about barriers that signifies involuntary exclusion such as the proximity, lack of required documentation, affordability, and lack of trust in the financial

system. Also, usage and access indicators specified by (Deepti and Vaidhyasubramaniam, 2018; Lyons and Kass-Hanna, 2019) were respectively utilized in the study.

2.2 Regional Based Studies on the Level of Financial Inclusion

(Rentala, Nandru and Anand, 2016) explored the status of financial inclusion among all South Asian Association for Regional Cooperation (SAARC) nations with descriptive statistics (percentage analysis), by using FAS data. The study which was conducted for the period of 2004 to 2014 adopted the indicators used by (Ayoola *et al.*, 2019), and further included number of insurance policies. It was observed that the percentage of adults who have accounts increased from 32 percent in 2011 to 46 percent in 2014, and the penetration of insurance products as well as use of digital payments were very low in SAARC countries during the study period. The research showed that there was disparity between having a bank account and usage of the financial services. Overall results indicated that bank branches, ATM penetration as well as the use of mobile money accounts have significant impact on access and use of banking services. Hence, they can be considered as determinants of financial inclusion outreach in SAARC nations. Unavailable data for certain countries regarding some indicators was the limitation for this research.

Just as (Ozili, 2020) proposed, (Rentala, Nandru and Anand, 2016) also emphasized that future researchers have an opportunity to investigate and compare financial inclusion among different regional blocs across the globe, particularly their determinants of financial inclusiveness, as it will assist policy makers to initiate measures that will increase inclusive finance in several countries so as to fulfil the World Bank's vision of achieving universal financial access by 2020.

An insight to the level of financial inclusion in different developing regions around the world for the year 2014 was provided by (Jukan and Softic, 2016). Regions such as Eastern, South and Central Asia, Latin America, Sub-Saharan Africa, and the Western Balkans were examined in light of the fact that population of those regions is at the highest risk of being financially excluded. Having obtained secondary data from the Global Findex database, it was discovered that Eastern Asia had the highest level of formal account usage and savings with 69% and 37% of its populace using formal account and having savings at financial institution, respectively. While the degree of formal account usage in Sub-Saharan Africa was the lowest at 34.20%, Central Asia also had the lowest amount of population who own a formal savings at 8%. Western Balkans reported the highest level of borrowing and the lowest level was at Sub-Saharan Africa and South Asia. Asides Eastern Asia having the highest level of account usage, the region also recorded the highest usage of debit card at 43%, while Sub-Saharan Africa and South Asia remained at the bottom at 18%. Mobile money is often used in Sub Saharan Africa because in Africa, bank branches and ATMs are usually far from the place users live, and since a huge area has wireless internet connection, mobile phone is easier to use for financial transactions. However, Central Asia maintained the bottom in terms of mobile money as well.

(Wang and Guan, 2017) found out Europe and North America enjoy higher levels of financial inclusion compared to the less developed African countries and most of Asia. Also, it was deduced that financial inclusion improvement in one country has spillover effects on neighbouring countries. Thus, close countries will impact one another. Evident from the work of (Jukan and Softic, 2016; Wang and Guan, 2017), (Chinoda and Kwenda, 2019) identified Eastern Asia and Europe as regions with higher levels of financial inclusion. Moreover,

Africa was regarded as a region that needs immediate attention in terms of financial inclusion.

The level of financial inclusion in 22 Sub-Saharan Africa countries between 2005-2015 was investigated by (Ayoola *et al.*, 2019) using FAS data. The research which aimed to determine the level of adult financial inclusion in Sub-Saharan Africa was subjected to Principal Component Analysis (PCA). The result showed that British colonized countries in the region are less financially included than their French counterpart. Seychelles was reported to have the highest level of financial inclusion, while Gabon had the lowest among the observed Sub-Saharan African countries. Aggregate result identified Sub-Saharan Africa as a region with medium level of financial inclusion and in line with (Sha'ban, Girardone and Sarkisyan, 2020), financial inclusion in the region was perceived to have attained steady improvement over the period of study. (Asuming, Osei-Agyei and Mohammed, 2019) discovered that between 2011 and 2014, Southern African countries have the highest level of financial inclusion, followed by East African and then, Central African countries, but West African countries have the lowest degree of inclusive finance.

2.3 Country Based Research on the Level of Financial Inclusion

(Adalessossi and Kaya, 2015; Chinoda and Kwenda, 2019), both obtained data from Global Findex database to assess the financial inclusion condition in Africa but applied different approach. While the former considered discriminant analysis as the ideal and reliable statistical method for evaluating the level of financial inclusion in 41 countries, the latter computed an index of financial inclusion for 49 countries and used PCA in aggregating each indicator to a dimension index, just like (Cámara and Tuesta, 2014; Datta and Singh, 2019). The information derived by the former with the aid of SPSS 20.0 revealed that 27 countries have a low level of financial inclusion and 14 countries have high level of financial inclusion. However, the analysis was successful using discriminant analysis because the correct classification of the result accounted for 92.7% (Adalessossi and Kaya, 2015). On the other hand, (Chinoda and Kwenda, 2019) which followed the steps of (Park and Mercado, 2018) in making analysis based on access, availability, and usage identified that, amongst the 49 African countries that were considered over the period of 2004-2016, only Seychelles and Cape-Verde had an average financial inclusion index above 50 percent, and the rest were below 40 percent. One limitation of (Park and Mercado, 2018) that was addressed by (Chinoda and Kwenda, 2019) is that the former did not include deposit to its indicators but the latter did because deposit is an important indicator of the usage dimension (Deepti and Vaidhyasubramaniam, 2018).

The number of debit and prepaid cards per capita are not usually considered when financial inclusion is estimated but was included in (Nuzzo and Piermattei, 2020) research. Although, many researchers collected data from Findex and/or FAS, but the study went further by adding a third source, the Euro area payment statistics. Reason being that diffusion of electronic payment which has generally not been included in financial inclusion indexes was the focus of the research. Principal component analysis carried out on the commonly used dimensions of financial inclusion identified Spain and Germany as the highest and lowest financially inclusive countries respectively, for the study period of 2007-2016. Whereas result obtained from the inclusion of number of debit and prepaid cards per capita but with the exclusion of credit related variables, identified Germany as the best performing country in terms of financial inclusion and Italy as the worst. The inclusion of new relevant indicators to

the measurement of financial inclusion makes the index more comprehensive and not detrimental(Goel and Sharma, 2017; Yorulmaz, 2018).

3 Research Methodology

An accurate and complete description of the selected data, research procedure and techniques used in this study are provided in this chapter, following the Knowledge Discovery in Database (KDD) approach.

3.1. Data Selection

Findex and FAS database are the two major data collection initiatives for financial inclusion. They provide useful insights concerning the degree of inclusiveness of financial systems. However, if used individually, they will produce only partial information on the overall inclusiveness of financial systems and that can lead to misinterpretation of the extent of financial inclusion in a given country (Nuzzo and Piermattei, 2020). The empirical analysis in this study used both World bank Global Findex data and IMF Financial Access Survey data. However, for the purpose of this research, only member countries of the regional blocs in Africa with data available in both datasets over the period of 2011, 2014 and 2017, were considered.

The following subsections contributed to the construction of the dataset.

3.1.1 Africa's regional blocs and their member states

The eight regional blocs and their respective member states in Africa are[4]:

Table 1: List of countries that make up each regional bloc in Africa

Regional blocs	Member states
Arab Maghreb Union (AMU)	Algeria, Libya, Mauritania, Morocco, and Tunisia.
Community of Sahel–Saharan States (CEN-SAD)	Benin, Burkina Faso, Central African Republic, Chad, Comoros, Cote d'ivoire, Djibouti, Egypt, **Gambia,** Ghana, **Guinea Bissau**, Libya, Mali, Mauritania, Morocco, Niger, Nigeria, **Eritrea**, Senegal, Sierra Leone, **Somalia**, Sudan, Togo, and Tunisia.
Common Market for Eastern and Southern Africa (COMESA)	Burundi, Comoros, Democratic Republic of Congo, Djibouti, Egypt, **Eritrea**, Ethiopia, Kenya, Libya, Madagascar, Malawi, Zimbabwe, Mauritius, Rwanda, Sudan, Swaziland, **Seychelles**, Uganda, and Zambia.
East African Community (EAC)	Burundi, Kenya, Rwanda, South Sudan, Uganda, and United Republic of Tanzania.

[4] https://www.uneca.org/oria/pages/regional-economic-communities

Economic Community of Central African States (ECCAS)	Angola, Burundi, Cameroon, Central African Republic, Chad, Congo, Democratic Republic of Congo, **Equatorial Guinea**, Gabon, Rwanda, and **Sao Tome and Principe**.
Economic Community of West African States (ECOWAS)	Benin, Burkina Faso, **Cabo Verde**, Cote d'ivoire, **Gambia**, Ghana, Guinea, **Guinea Bissau**, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, and Togo.
Intergovernmental Authority on Development (IGAD)	Djibouti, Ethiopia, **Eritrea**, Kenya, **Somalia**, Sudan, South Sudan, and Uganda.
Southern African Development Community (SADC)	Angola, Botswana, Democratic Republic of Congo, Comoros, Lesotho, Malawi, Mauritius, Mozambique, Namibia, **Seychelles**, South Africa, Swaziland, Tanzania, Zambia, Zimbabwe, and Madagascar[5]

The countries in bold text were excluded from this analysis because of the following reasons. Data for Gambia, Guinea Bissau, Eritrea, Sao Tome and Principe, Seychelles, Equatorial Guinea, and Cabo Verde are available in FAS but not in Findex. This implies there are supply side but no demand side data for the countries listed. Also, data for Somalia is available in Findex but not in FAS. 46 countries out of the 54 African countries[6][7] were included in this paper.

3.1.2 Dimensions and Data sources

Following existing literatures which are in line with World bank and Global Partnership for Financial Inclusion (GPFI) on the dimensions of inclusive finance, financial inclusion in this study was measured by three dimensions: usage, access, and quality[8][9], of which the dimensions were determined by a set of 24 indicators.

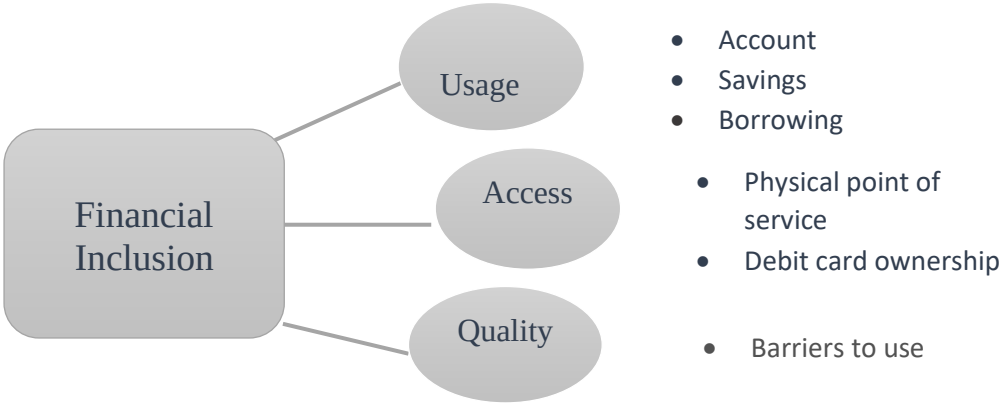

Figure 1: Dimensions and indicators of financial inclusion.

[5] https://www.sadc.int/member-states/comoros/
[6] https://www.worldometers.info/geography/how-many-countries-in-africa/
[7] https://www.nationsonline.org/oneworld/africa.htm
[8] https://www.worldbank.org/en/topic/financialinclusion/brief/how-to-measure-financial-inclusion
[9] https://www.gpfi.org/sites/gpfi/files/G20%20Set%20of%20Financial%20Inclusion%20Indicators.pdf

The indicators for the dimensions in this study were obtained from FAS and Findex over the period of 2011, 2014 and 2017. FAS is a supply side panel dataset that provides data concerning access and use of financial services. It covers 189 countries with 64 indicators in relation to the size of adult population, land area and gross domestic product[10]. Findex is the world's most comprehensive demand side panel dataset on adult's attitude to savings, borrowing, payment and risk management. The data which is disaggregated by demographic characteristics covers nationally representative survey of about 150,000 randomly selected adults in more than 140 economies and it is recorded on a triennial basis, starting from 2011[11].

Usage indicators considered in this study encompasses accounts, which include; the percentage of respondents (age 15 and above) who have an account by themselves or jointly with someone else at any financial institution, those who made deposit or withdrawal with their account by themselves or together with someone else in the past 12 months (active account), the total number of deposit accounts owned by corporations and households in commercial banks for every 1,000 adults, mobile money transactions per 100,000 adults, those who made or received digital payment from an account and those individuals who are regarded as indirect users of formal financial services because they stated not having a bank account since another person in the family already has one (Cámara and Tuesta, 2014). Also, the adult population that saved at a financial institution and saved for old age in the past year represent savings[12], while those who borrowed from financial institution as well as number of outstanding loans represent borrowing[13]. It is important to note that data on digital payments includes those who used phone and/or internet to pay bills or make purchases online, the people that sent or received money from a bank account, other formal financial institution or mobile money provider, those who used debit or credit card to make a direct payment from an account, sent or received remittances to or from an account, received wages, government transfer payments, or agricultural payments to an account and paid utility or school fees from an account(Demirguc-Kunt *et al.*, 2018). The data was obtained from both Findex and FAS data.

Access dimension measures the depth of outreach of financial services[14]. In this research, it was estimated with physical point of service indicators such as Automated teller machine (ATM) per 100,000 adults, ATM per 1,000km^2, commercial bank branches per 100,000 adults, commercial bank branches per 1,000km^2 and mobile money agent outlet. Debit card ownership was also considered an indicator of this dimension[15]. The data was collected from FAS[16].

Quality was measured on the basis of usage barrier. To measure financial inclusion, from the unbanked perspective, only the information about barriers that has to do with involuntary exclusion such as distance, lack of the necessary documentation, affordability and lack of trust in the financial system was considered in this research. The question in relation to barriers is drafted in the Global Findex questionnaire in such a way that individuals can

[10] https://data.imf.org/?sk=E5DCAB7E-A5CA-4892-A6EA-598B5463A34C&sId=1412015057755
[11] https://globalfindex.worldbank.org/
[12] https://databank.worldbank.org/data/download/g20fidata/G20_Financial_Inclusion_Indicators.pdf
[13] https://databank.worldbank.org/data/download/g20fidata/G20_Financial_Inclusion_Indicators.pdf
[14] https://www.worldbank.org/en/topic/financialinclusion/brief/how-to-measure-financial-inclusion
[15] https://databank.worldbank.org/data/download/g20fidata/G20_Financial_Inclusion_Indicators.pdf
[16] https://data.imf.org/?sk=E5DCAB7E-A5CA-4892-A6EA-598B5463A34C&sId=1460043522778

choose different reasons for not having a bank account(Cámara and Tuesta, 2014). The information was gathered from Global Findex data[17].

3.2 Pre-Processing

This entails cleaning and organizing the selected datasets to make them suitable for extracting meaningful insights[18]. Here, both data were collected and imported from their respective online sources to R studio in csv format, countries that make up the regional blocs in Africa were checked for data availability in both datasets. The variables that are not considered as indicators of financial inclusion in this study were removed, likewise, the countries which do not belong to the member states of Africa's regional blocs and those not present in both datasets. The structure of both data were examined. Missing values and outliers were identified and correctly handled.

3.3 Data Transformation

After cleaning both data, they were transformed into forms appropriate for data mining. Here, some variables were renamed and reordered. As two datasets sourced from different database were considered relevant for this study, they were both merged to form a whole data.

3.4 Data mining

Data mining identifies the pattern and hidden information in a data[19]. This study used the technique stated below.

3.4.1 Robust Principal Component Analysis (RPCA)

Principal component analysis (PCA) is a multivariate technique for data analysis. It explains the overall variance in a data by using orthogonal combinations of the principal component variables[20]. A modification to PCA which is robust to outliers and can work with corrupted data is called robust PCA[21]. This research utilized the modified PCA because, one of the assumptions of principal component analysis is that there must be no outliers in the data as it can negatively impact the result. However, in the real world, the data points identified as outliers might be useful for the research. So, instead of getting rid of them, this study finds it appropriate to use a technique that will not be negatively affected by the presence of outliers. In respect to that, a robust PCA technique called Principal component analysis on Covariance matrix (PcaCov) was used, as against other researchers which used the classical PCA.

3.5 Evaluation of result

The different regions were ranked based on their estimated index score for access, usage, and quality of financial service. Afterwards, their overall financial inclusion index score were

[17] https://globalfindex.worldbank.org/
[18] https://towardsdatascience.com/data-preprocessing-concepts-fa946d11c825
[19] https://www.sas.com/en_ie/insights/analytics/data-mining.html
[20] https://www.math.uci.edu/icamp/courses/math77b/lecture_12w/pdfs/PCA.pdf
[21] https://en.wikipedia.org/wiki/Robust_principal_component_analysis

used to rank and compare their level of financial inclusion. To ascertain a systematic analysis, values above 0.6 – 1 were considered as indicative of high inclusive finance, those values that were within the range of 0.3 - 0.6 were considered medium financial inclusion while values between 0 - 0.29 were termed low financial inclusion (Datta and Singh, 2019). Also, values less than 0 were considered very low and those greater than 1 were considered very high.

4 Model Specification

Financial inclusion should be determined by the interaction of causal variables because it is an unobservable concept that cannot be quantitatively measured in a straightforward manner (Cámara and Tuesta, 2014). As such, the selected dataset for this study consists of causal variables that summarize the information for the degree of financial inclusion. As explained in the data selection, the variables in the selected dataset are indicators of the different financial inclusion dimensions. It is important to note that there is dual advantage in the division of the overall set of indicators into three dimensions. First, since the three dimensions are meaningful, relevant information that is useful for policy making can be deduced. On the other hand, for methodological purposes, since the dimensions consist of highly correlated indicators, the different dimensions are estimated first, instead of directly estimating the overall index by picking all the indicators at the same time. This is considered an appropriate strategy by (Datta and Singh, 2019) because it avoids weight biases towards highly correlated indicators. Unlike (Datta and Singh, 2019) which followed the view of (Cámara and Tuesta, 2014) to apply two-stage PCA in that regard, this study employed two-stage robust PCA for analysis. While the estimation of the three dimensions: access, usage and quality occurred in the first stage robust PCA, the second stage entailed computing the overall financial inclusion index by using the dimensions as explanatory variables.

Financial inclusion is linearly determined as follows:

$$FI_{r,p} = \omega_1 A^a_{r,p} + \omega_2 A^u_{r,p} + \omega_3 A^q_{r,p} + e_{r,p} \qquad (1)$$

Here, subscript r and p denote the region and period respectively, while $(A^a_{r,p}, A^u_{r,p}, A^q_{r,p})$ represent access, usage and quality dimension respectively. The variation due to the causal variables and error term $(e_{r,p})$ are the contributing factors to the total variation in financial inclusion. However, if there is a well specified model, with an adequate number of explanatory variables, E(e) = 0 and the error term will have a relatively small variance compared to that of financial inclusion. Hence, it can be reasonably presumed that the total variation in financial inclusion can largely be explained by the variation in the causal variables.

4.1 First stage RPCA

This stage provided estimate of the three dimensions using the following equations.

$$A^a_{r,p} = \gamma_1 ATM.pop_{r,p} + \gamma_2 ATM.km_{r,p} + \gamma_3 branch.pop_{r,p} + \gamma_4 branch.km_{r,p} + \gamma_5 outlet_{r,p} + \gamma_6 debitcard_{r,p} + u_{r,p} \qquad (2)$$

$$A^u_{r,p} = \beta_1 account_{r,p} + \beta_2 savings_{r,p} + \beta_3 loan_{r,p} + v_{r,p} \qquad (3)$$

$$A^q_{r,p} = \theta_1 trust_{r,p} + \theta_2 distance_{r,p} + \theta_3 affordability_{r,p} + \theta_4 documentation_{r,p} + \theta_1 fund_{r,p} + \epsilon_{r,p} \qquad (4)$$

The three dimensions were estimated by robust PCA as linear function of their respective indicators as explained in section 3.1.2. In equation 5,6 and 7 respectively, λ_j^a (j = 1, 2, 3,4,5,6) is denoted as the jth eigen value for access, λ_j^u (j = 1, 2, 3) is the jth eigen value for usage and λ_j^q (j = 1, 2, 3,4,5) is denoted as the jth eigen value for quality. Subscript *j* refers to the number of principal components that also coincides with the number of indicators. Also, P_k (k= 1,...,n) is denoted as the kth principal component. From the formula, it is obvious that the P_k value is what differentiates the estimate for each region during a period, as the value for λ_j remain constant in each dimension. The estimation for each dimension was derived from the following weighted averages:

$$A_{r,p}^a = \frac{\sum_{j,k=1}^{p} \lambda_j^a P_{kr,p}^a}{\sum_{j=1}^{p} \lambda_j^a} \qquad (5)$$

$$A_{r,p}^u = \frac{\sum_{j,k=1}^{p} \lambda_j^u P_{kr,p}^u}{\sum_{j=1}^{p} \lambda_j^u} \qquad (6)$$

$$A_{r,p}^q = \frac{\sum_{j,k=1}^{p} \lambda_j^q P_{kr,p}^q}{\sum_{j=1}^{p} \lambda_j^q} \qquad (7)$$

Here, $P_k = X\lambda_j$. However, λ_j is the variance of the kth principal component (weights) and *X* is the indicators matrix. The values for $P_{kr,p}$ were obtained from the robust PCA scores. An issue with using principal component analysis is having to determine the number of components to retain. Although, replacing the causal variables by just the first few principal components that account for a substantial amount of the total variation is a common approach. That was not the case in this study because the concern was to correctly measure financial inclusion. So, rather than performing dimensionality reduction, as many components as the number of explanatory variables were considered so as to prevent getting rid of information that might affect the estimate.

4.2. Second stage PCA

The overall financial inclusion index was computed in this stage. Here, the variables under consideration were the three estimated dimensions ($A_{r,p}^a$, $A_{r,p}^u$, $A_{r,p}^q$). By following the same procedure as that of the first stage to determine the parameter λ_j, financial inclusion index can be defined as:

$$FI_{r,p} = \frac{\sum_{j,k=1}^{p} \lambda_j P_{kr,p}}{\sum_{j=1}^{p} \lambda_j} \qquad (8)$$

In equation 8, P_k was estimated as the linear combination of the three dimensions (p = 3) and the eigenvectors or loadings of the respective correlation matrices denoted with φ:

$$P_{1r,p} = \varphi_{11} A_{r,p}^a + \varphi_{12} A_{r,p}^u + \varphi_{13} A_{r,p}^q \qquad (9)$$

$$P_{2r,p} = \varphi_{21} A_{r,p}^a + \varphi_{22} A_{r,p}^u + \varphi_{23} A_{r,p}^q \qquad (10)$$

$$P_{3r,p} = \varphi_{31} A_{r,p}^a + \varphi_{32} A_{r,p}^u + \varphi_{33} A_{r,p}^q \qquad (11)$$

Hence, financial inclusion index can be defined as:

$$FI_{r,p} = \frac{\sum_{j=1}^{3} \lambda_j (\varphi_{j1} A_{r,p}^{a} + \varphi_{j2} A_{r,p}^{u} + \varphi_{j3} A_{r,p}^{q})}{\sum_{j=1}^{3} \lambda_j} \qquad (12)$$

The financial inclusion index for the various regional blocs was computed using equation 12.

5 Implementation

5.1. Data Selection

This research collected and imported financial inclusion data from two different sources: World bank's Findex and IMF's FAS data, into R studio. Both datasets were downloaded in csv format and saved in the document folder before importing to R. While the former contains triennial data with 494 observations and 781 variables for 2011-2017, the latter contains annual data with 2835 observations and 188 variables for 2004-2018. However, given that this study focused on measuring the extent of financial inclusion among regional blocs in Africa for the period of 2011, 2014 and 2017, only the member countries of Africa's regional blocs and the relevant variables for measuring financial inclusiveness as discussed in section 3.1.1 and 3.1.2 were selected over the period under consideration. This led to a reduction in the Findex data to 114 observations and 16 variables, while FAS data reduced to 138 observations and 10 variables.

5.2 Data Pre-processing and Transformation

Here, both datasets were initially pre-processed and transformed individually. Afterwards, they were merged into one dataset. The following explains the procedures carried out.

5.2.1 Findex data (Dataset 1)

The first two columns that indicates year and economy, were renamed appropriately. The removal of unwanted rows (i.e. countries that do not belong to the scope of this research and those not present in FAS data) resulted to improper numbering of the index. However, that was treated by re-ordering the row index numbers in ascending order. Unlike FAS data, this dataset contains the symbol – (%), depicting values in percentage. For this analysis, the symbol was removed, and the values were converted to decimal by dividing through by hundred. It is important to state that before the conversion to decimal, the structure of the dataset was checked, and the numeric variables were transformed from character to numeric, while the variables: year and economy were not changed from their original form, character.

Eswatini, which was formally called Swaziland has its data collected as 'Swaziland' in the dataset. This was addressed by changing the name to Eswatini. Also, to ensure uniformity, Egypt, Republic of Congo, and Democratic Republic of Congo were renamed or re-written as they appear in FAS data.
There was 35.7% missing and 64.3% present data identified in the dataset. It is evident from figure 2 that there is a pattern to the missingness, thus, making it missing at random.

Nonetheless, missing data was not treated at an individual stage as the goal was to merge both Findex and FAS dataset into a whole data. Outliers were found in the data.

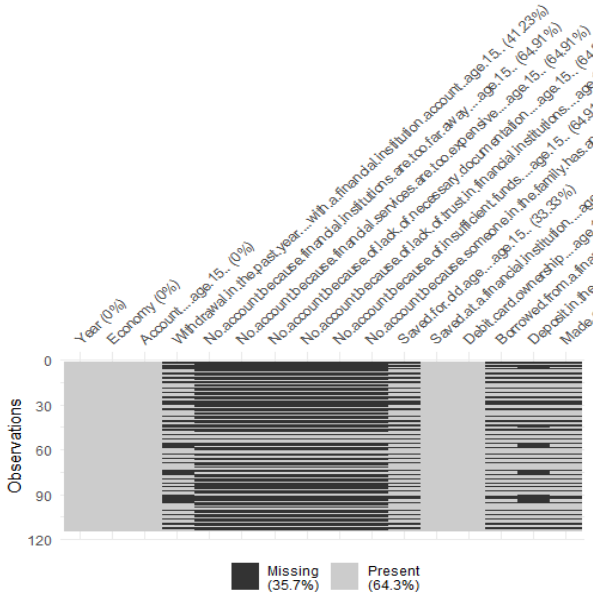

Fig.2. Missingness plot for Findex data

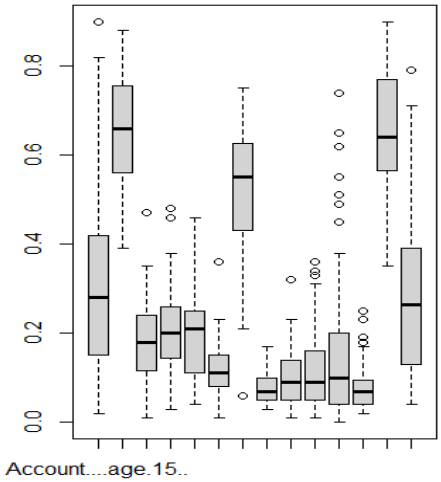

Fig.3 Box plot for Findex data

5.2.2 FAS data

The first two columns were re-arranged like the first data, so that year variable would come before economy. Similar to the first data, Findex, the removal of unwanted rows (i.e. countries that do not belong to the scope of this research, those not present in Findex data and data for years other than 2011, 2014, and 2017) resulted to improper numbering of the index but that was treated by re-ordering the row index numbers in ascending order. Having identified what the structure of the dataset is, it was discovered that every other variable aside 'year' were originally stored as their appropriate data type. However, variable year was converted from integer to character.

NAs identified in variables that have to do with mobile money indicates that there are no mobile money services in the country[22]. The metadata on the other hand countered that by revealing that not all countries with NAs in those variables have no mobile money service. Hence, the NAs in both mobile money agent outlet and mobile money transactions were converted to zero (no mobile money service), with the exclusion of those countries identified in the metadata to have started mobile money services but have missing values. Table 2 contains details of those countries whose NA values in mobile money were not all converted to zero.

[22] https://data.imf.org/?sk=E5DCAB7E-A5CA-4892-A6EA-598B5463A34C&sId=1390030341854

Table 2: Details of those countries whose NA values in mobile money were not all converted

Countries	Mobile money operation	Approach taken
Benin	Started in 2010	NA found in 2011, 2014 and/or 2017 were not converted to zero as they are regarded as missing values.
Botswana	Started in 2010	Same as above
Burkina Faso	Started in 2011	Same as above
Burundi	Exists but statistics are not produced because there is no legal basis	Same as above
Cote d'ivoire	Started in 2008	Same as above
Ghana	Started in 2009	Same as above
Liberia	Launched in 2011	Same as above
Mali	Started in 2010	Same as above
Mozambique	Started in 2011	Same as above
Niger	Began in 2009	Same as above
Nigeria	Began in 2010	Same as above
Senegal	Started in 2008	Same as above
Tanzania	Started in 2009	Same as above
Zimbabwe	Started in 2008	Same as above
Chad	Started in 2013	Only the NA found in 2011 was converted to zero. NAs in 2014 and 2017 were regarded as missing values
Egypt	Started in 2013 but data are available from 2015	Same as that of Chad
Mauritania	Started in 2013	Same as that of Chad
Mauritius	Started in 2013	Same as that of Chad
South Africa	Due to confidentiality reason, data was not available up until 2013 onward. No data since 2017 because service providers discontinued operation in 2017.	NA found in 2011 and 2014 were termed as missing values. For 2017, the NA value was changed to zero.

Source: FAS metadata[23]

[23] https://data.imf.org/regular.aspx?key=61063980

Like Findex data, the 13.8% missing values were not treated. Handling of the missing values were treated after merging both datasets, likewise the outliers present in the data.

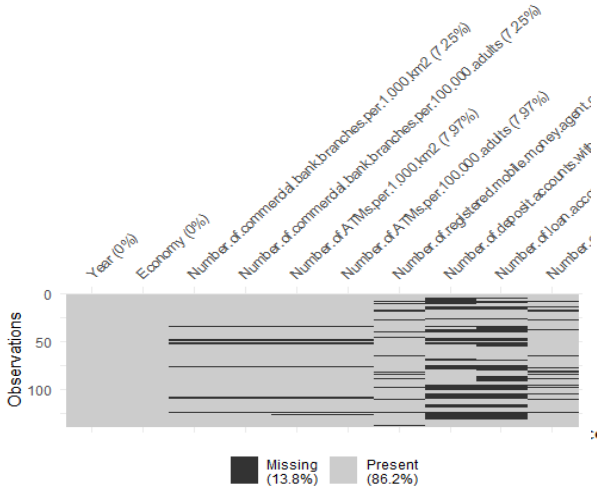

Fig.4. Missingness plot for FAS data

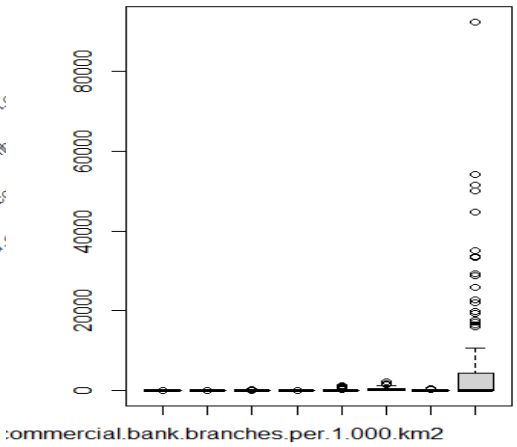

Fig.5. Box plot for FAS data

5.2.3 Merged data

After pre-processing and transforming the two datasets individually, they were merged by year and economy, thereby producing one dataset with 138 observations and 24 variables. However, as thorough examination of the missing data is a vital aspect of exploratory data analysis, this research attempted to examine the degree and pattern of missingness in the data as that would give an insight concerning the appropriate technique for handling the missing values.

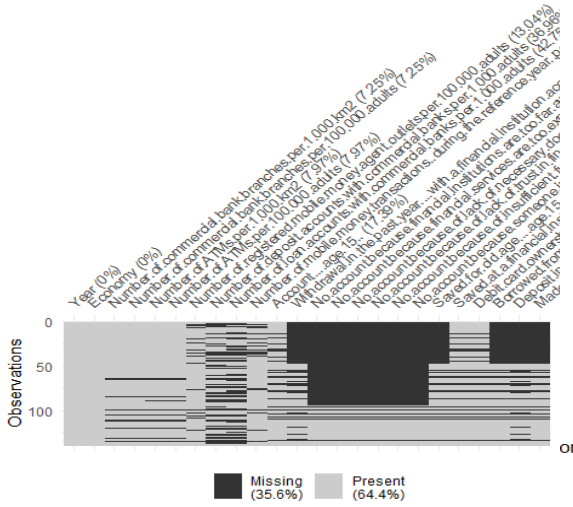

Fig.6. Missingness plot for merged (Findex and FAS) data

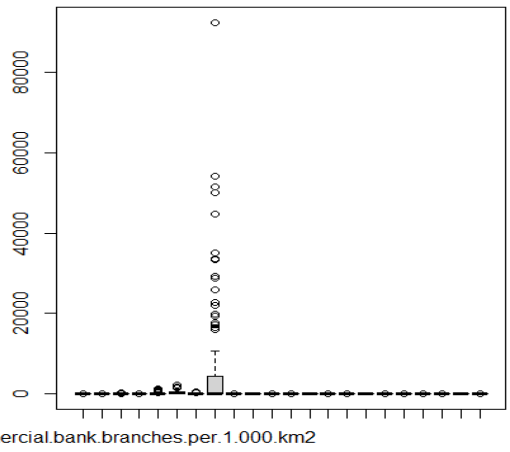

Fig.7. Box plot for merged data

As shown in figure 6, the merged data contained 35.6% missing values. All variables except year and economy had missing values. Also, since there is a pattern to the missingness, the assumption was that the data are missing at random. Thus, this study used Probabilistic Principal Component Analysis (PPCA) for imputation. PPCA which uses Expectation–Maximization (EM) algorithm to iteratively compute the Maximum Likelihood Estimates (MLE) of an incomplete data set, can be performed if data is missing at random and if there is a high proportion of missingness up to 50% (Hegde *et al.*, 2019). For the imputation, the number of principal components was first determined using kfold 'estim_ncpPCA' function. The process of imputation identified a row which contained only missing values. The row in question was that of Burundi for the year 2017. In respect to that, the row was excluded for the imputation and further analysis because PPCA failed to impute when a row contained only missing values. This reduced the number of observations by one and led to reordering of the row index numbers.

After imputation, a new variable called 'region' which indicates the regional bloc each country belongs to was created and the countries which make up each regional bloc were added up by year. Thereby, reducing the number of observations to 24, i.e. 3 years (2011, 2014 and 2017) for each of the 8 regional blocs. Prior to that, feature engineering was carried out by creating three new variables from some of the existing ones. The new variables created were account, loan, and savings. Active account (withdrawal and deposit in the past year), number of deposit account, mobile money transactions, adults with an account, made or received digital payment in the past year and indirect users of an account, i.e. those who reported not having an account because someone in the family does have an account were summed up to create the new variable, account. Save for both old age and at a financial institution represented the new variable, savings, while number of loan account and borrowed from a financial institution or used a credit card made up the new variable, Loan. To avoid duplicate, the variables which were added up to create new ones were removed from the dataset. Hence, reducing the number of variables from 25 to 16.

5.3 Data Mining

A correlation matrix of the dataset was created to perform Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) test to determine the suitability of the data for principal component analysis (PCA). Bartlett's test produced a p-value less than 0.05 and KMO had an overall measure of sampling adequacy of 0.79. Having determined the suitability of the data, robust principal component analysis which is robust to outliers was carried out. The first stage robust PCA was based on the three dimensions of financial inclusion; access, usage, and quality. This implies that, robust PCA was separately carried out on each of the three dimensions, respectively. Scaling function in the package was utilized to ensure normalization of the data. For the first stage robust PCA, the eigenvalues (λ_j) as well as the scores ($P_{kr,p}$) derived from 'PcaCov' were substituted in equation 5,6 and 7 to estimate each of the dimensions for the regional blocs at specific period. The values obtained from the 'scores' refer to the principal components for each of the regional blocs over the period of 2011,2014 and 2017.

In respect to the second stage robustPCA, a new dataset which consists of the values obtained from the first stage PCA was created. The values in question are the estimated values of the three financial inclusion dimensions for each of the regional blocs over the period of 2011, 2014 and 2017 ($A^a_{r,p}$, $A^u_{r,p}$, $A^q_{r,p}$). Thus, the new dataset was made up of 24 observations (8 regions for 3 years) and 5 variables (region, year, access, usage, and quality).

Robust principal component analysis was carried out on the new data. The eigenvalues of the principal components as well as the loadings of the correlation matrices and estimated value of the three financial inclusion dimensions for each of the regional blocs over the period were substituted in equation 9,10,11 and 12 to compute the overall financial inclusion index for the respective regional blocs over the considered period.

6 Evaluation of Result, Discussion and Limitation

6.1 Result

Table 4, 5 and 6 present the results derived from the first stage robustPCA. The tables show the ranking of the eight regional blocs in Africa by their degree of access, usage, and quality of financial inclusion over the years 2011,2014 and 2017. The ranking and determination of their level was based on their respective scores.

Table 3. Criteria for determining the level of financial inclusion.

Very low	Low	Medium	High	Very high
Score < 0	0 < = Score < 0.3	0.3 < = Score < = 0.6	0.6 < Score < = 1	Score > 1

Table 4. Regional blocs result for access dimension over the period of 2011, 2014 and 2017

Access

Region	2011			2014			2017		
	Score	Level	Rank	Score		Rank	Score	Level	Rank
AMU	-0.37725140	Very low	4	-0.19637690	Very low	6	-0.03171932	Very low	6
SADC	4.98315200	Very high	1	6.03537000	Very high	1	6.57241100	Very high	2
EAC	-0.80181090	Very low	6	-0.33094570	Very low	7	-0.16595420	Very low	7
ECCAS	-0.86932330	Very low	7	-0.07802531	Very low	5	-0.38112330	Very low	8
ECOWAS	-0.60812680	Very low	5	0.30908750	Medium	4	1.44767400	Very high	4
CEN-SAD	1.19314000	Very high	3	2.3291140	Very high	3	3.83448200	Very high	3
COMESA	4.21772300	Very high	2	5.47532900	Very high	2	6.87045500	Very high	1
IGAD	-1.15313700	Very low	8	-0.66634510	Very low	8	0.24874940	Low	5

Table 5. Regional blocs result for usage dimension over the period of 2011, 2014 and 2017

Usage

Region	2011			2014			2017		
	Score	Level	Rank	Score	Level	Rank	Score	Level	Rank
AMU	-0.72588890	Very low	5	-0.72720840	Very low	7	-0.58034660	Very low	8
SADC	0.77732740	High	1	1.22759700	Very high	1	1.75223500	Very high	2
EAC	-0.82573150	Very low	6	-0.12842680	Very low	4	0.07153594	Low	5
ECCAS	-0.84953940	Very low	7	-0.72855300	Very low	8	-0.43630770	Very low	7
ECOWAS	-0.47289390	Very low	4	-0.25699360	Very low	5	0.76004740	High	4
CEN-SAD	0.27419320	Low	2	0.50617770	Medium	3	1.64930500	Very high	3
COMESA	0.21967310	Low	3	0.76419390	High	2	1.91744700	Very high	1
IGAD	-0.90021820	Very low	8	-0.51943800	Very low	6	-0.11921230	Very low	6

Table 6. Regional blocs result for quality dimension over the period of 2011, 2014 and 2017

Quality

Region	2011			2014			2017		
	Score	Level	Rank	Score	Level	Rank	Score	Level	Rank
AMU	-1.7238470	Very low	8	-1.7497390	Very low	8	-1.9285790	Very low	8
SADC	0.6538879	High	3	0.2439152	Low	4	0.9414272	High	3
EAC	-1.2801530	Very low	7	-1.5178170	Very low	7	-1.6205900	Very low	7
ECCAS	-0.3011773	Very low	5	-0.6523402	Very low	5	-0.5597136	Very low	5
ECOWAS	0.5847649	Medium	4	0.3390339	Medium	3	0.3759769	Medium	4
CEN-SAD	2.8216850	Very high	1	2.4329770	Very high	1	2.4992190	Very high	1
COMESA	1.6606830	Very high	2	1.0920670	Very high	2	1.1068440	Very high	2
IGAD	-1.2201800	Very low	6	-1.3837620	Very low	6	-1.3689900	Very low	6

The results obtained from the second stage robust PCA are presented in table 7. It contains the ranking position, levels, and comparison of the regions according to their financial inclusion index score for the year 2011, 2014 and 2017.

Table 7. Financial inclusion result for the regional blocs over the period of 2011, 2014 and 2017

FII

Region	2011			2014			2017		
	Score	Level	Rank	Score	Level	Rank	Score	Level	Rank
AMU	-0.4150803	Very low	4	-0.3375675	Very low	6	-0.1657255	Very low	7
SADC	2.478066	Very high	1	3.220945	Very high	1	3.684578	Very high	2
EAC	-0.6939384	Very low	6	-0.06724345	Very low	5	0.1283624	Low	6
ECCAS	-0.8304604	Very low	7	-0.3945311	Very low	7	-0.3600916	Very low	8
ECOWAS	-0.586841	Very low	5	-0.05298401	Very low	4	1.013411	Very high	4
CEN-SAD	0.3878092	Medium	3	1.036483	Very high	3	2.327238	Very high	3
COMESA	1.735228	Very high	2	2.634399	Very high	2	3.889826	Very high	1
IGAD	-0.8903469	Very low	8	-0.4486375	Very low	8	0.1666765	Low	5

6.2. Discussion

In terms of access to financial inclusion, the regional economic blocs recorded improvement in 2017 over that of 2011 and 2014, except ECCAS which declined in 2017. The decline could be the resultant effect of Burundi which is one its member states that was not included in 2017 data because it had all NA values. However, Burundi is also a member of COMESA and EAC, but a better performance was reported in those regions in 2017. Despite the improvement among the seven other blocs, AMU and EAC maintained a very low level of financial access, like ECCAS. On the other hand, SADC, CEN-SAD, and COMESA had a very high level of access over the period. Interestingly, COMESA outperformed SADC in 2017 to top the list but CEN-SAD remained at the third place. Also, ECOWAS and IGAD achieved a significant improvement over the years. From a very low level, ECOWAS advanced to medium and very high level in 2014 and 2017, respectively. Moreso, IGAD developed from very low in 2011 and 2014 to a low level in 2017. In comparison to other regions, AMU, SADC, EAC and ECCAS's ranks declined, while the rest were either maintained or increased.

For usage dimension, all the blocs experienced an improved performance in 2017 over that of 2011 and 2014, but AMU had a slight decline between 2011 and 2014. Just like access, AMU and ECCAS improved but still retained a very low level of financial service usage. IGAD which developed from very low to low level in terms of access, failed to improve significantly in respect to usage as it maintained a very low level of financial service usage over the years. Five out of the eight regions experienced a significant advancement in their levels over the years. SADC started off with a high level in 2011 but achieved a very high

degree in 2014 and 2017. However, EAC and ECOWAS which started from a very low level of usage in 2014 improved significantly at varying degrees. While EAC increased from very low level in 2011 and 2014 to a low level in 2017, ECOWAS attained a high level. Similarly, CEN-SAD and COMESA both experienced a low level of financial service usage in 2011, but as of 2014, the former attained a medium level while the latter experienced a high level of usage. Ultimately, they both attained a very high level in 2017. Just like the access to financial services, COMESA achieved a steady progress by outperforming CEN-SAD and SADC in 2014 and 2017, respectively.

Between 2011 and 2014, all the eight regions had a decline in their quality of financial services which was measured by the barriers to financial inclusion. Although, they maintained their respective levels despite the decline, except SADC which as a result of the decline, fell from a high to low level. Within 2014 and 2017, AMU and EAC's quality of service further decreased and they both occupied the 8th and 7th position, respectively. The other blocs however experienced an improvement, of which SADC bounced back to a high level but the rest retained their levels. Only COMESA and CEN-SAD had very high quality of financial services. While, AMU, EAC, ECCAS, and IGAD were stuck at a very low level, ECOWAS enjoyed a medium level of quality of financial services. The ranking position for this dimension was quite stable across the blocs over the period, except for SADC and ECOWAS which outperformed each other.

The blocs that consistently performed the least in relation to the three dimensions are AMU, EAC, ECCAS and IGAD. None of them attained a medium level, let alone a high level. The highest any of them attained was a low level, of which it was IGAD and EAC that achieved the low levels in 2017 for access and usage, respectively. The top four regions are COMESA, SADC, CEN-SAD, and ECOWAS. They all improved over the years from low levels to attain medium, high, and very high levels. While ECOWAS consistently maintained the 4th position across the three dimensions in 2017, COMESA and SADC respectively retained the 1st and 2nd position in terms of access and usage in 2017. But CEN-SAD took over the top position from COMESA in regards to quality, as the region had consistently topped the chart from 2011.

As regards the overall financial inclusion index, there has been a steady improvement across all the regional blocs in Africa for the period of 2011,2014, and 2017. Five out of the blocs experienced a low level of financial inclusion during the period, of which three of them had a very low level and two achieved a low level. The other three out of the eight regional blocs realized a very high level of financial inclusion. The three of them are COMESA, SADC and CEN-SAD which respectively attained the 1st, 2nd, and 3rd position in 2017. It is important to state that COMESA and SADC respectively occupied the 2nd and 1st position in 2011 and 2014 but took a different turn in 2017 when COMESA outperformed SADC. As for CEN-SAD, the 3rd position was retained all through. The effort of ECOWAS is highly commendable as the region moved from a very low level of financial inclusion in 2011 and 2014 to a very high level in 2017, thereby occupied the 4th rank.

The regional blocs that performed the least in relation to the three dimensions happened to remain the least four performing regions in terms of the overall financial inclusion. On the whole, it is observed that the regional blocs in Africa have improved over the years but only 4 of them (SADC, CEN-SAD, ECOWAS and COMESA) have attained a very high level of financial inclusion, 2 (EAC and IGAD) have improved to a low level, while the remaining

two, AMU and ECCAS are still left behind as they recorded very low financial inclusion levels.

Conclusively, only 4 regional blocs in Africa have achieved inclusive finance to a high extent. Moreover, previous researchers have identified the African region as that which needs proper attention in terms of financial inclusion. This research however identifies those regional blocs whose extent of financial inclusion are still on the low side i.e. AMU, EAC, ECCAS and IGAD as areas which need proper and immediate attention, to help boost the overall level of financial inclusion in Africa.

6.3. Limitation

This study was unable to include all the member countries for each of the regional blocs due to data unavailability. Only AMU was fully represented all through the period. EAC was fully represented, up until 2014, but as of 2017, the data for Burundi which is a member state was not available. For the other blocs, at most three of their member states were not included in the analysis. Also, the imputation by Probabilistic Principal Component Analysis (PPCA) returned a few negative values for the missing data points. Moreover, in real life scenario, negative values are not applicable to those data points. Multiple imputation would have been considered an alternative to PPCA but pooling of the imputed data sets does not apply to this study as there is no model of interest to fit the multiple imputed data for the purpose of pooling.

7 Conclusion and Future Work

In this paper, effort to measure the extent of financial inclusion among the eight regional blocs in Africa was achieved with two stage robust Principal Component Analysis (PCA). Findex and Financial Access Survey (FAS) data were utilized for the study. In the first stage robust PCA, the three dimensions of financial inclusion considered in this study; access, usage and quality, were estimated for each of the region over the period of 2011, 2014 and 2017. Afterwards, the overall financial inclusion index was measured for the blocs over the study period in the second stage robust PCA. The extent to which the various regional blocs are financially inclusive were determined by their respective index scores. The scores were also used to rank and make comparison amongst them. It was discovered that performance of majority of the blocs improved over the research period and in spite of that, four of the regional blocs (AMU, EAC, ECCAS and IGAD) encountered low level of financial inclusion and did not go beyond that. The other four blocs (SADC, CEN-SAD, ECOWAS and COMESA) attained a very high level of inclusive finance. Also, the ranking position of most of the regional economic blocs were not stable over time. The validity of the result is constrained by unavailability of data, as majority of the blocs were not fully represented by their member states. In addition, probabilistic PCA returned negative values for some of the missing data point, and that is not applicable in real life scenario. Future research should identify the demographic characteristics of the population that are financially inclusive against the ones that are not.

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