

Mapurita, Christian Kamenga; Mayoukou, Célestin

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Contribution to the measurement of digital financial inclusion in Sub-Saharan Africa

Christian Kamenga Mapurita^{a,b,*}, Célestin Mayoukou^a

^a Université de Rouen Normandie, Normandie Univ, LERN UR 4702, F-76000, Rouen, France

^b Université Nouveaux Horizons, Lubumbashi, Democratic Republic of the Congo

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ABSTRACT

Despite the notable progress made in the development of digital financial services in sub-Saharan Africa, no comprehensive measure is currently available to quantify this progress. Therefore, we constructed a digital financial inclusion index using a parametric approach. Our findings show an upward trend in digital financial inclusion from 2014 to 2021, with a notable increase observed in this index in 2021. Based on the instrumental variable approach, we found that COVID-19, growth product per capita, and quality of governance were the main drivers of digital financial inclusion. Furthermore, findings reveal that not all sub-Saharan African countries have benefited equally from the digital financial revolution. Some countries, including Kenya, Ghana, and Côte d'Ivoire, have benefited substantially because of their high degree of digital financial inclusion. However, other countries—such as Malawi, Guinea, Burkina Faso, and Mali—have fallen behind in terms of digital financial inclusion and are reaping fewer benefits from the revolution in digital banking. We interpreted this observation as symptomatic of inequality. Using the Shapley decomposition analysis, we found that 33% of the disparities in digital financial inclusion among the examined countries were attributable to differences in the use of digital financial services and 13% to the differences in access to those services. We identified the legal origin as a driver of inequality in both access to and use of digital financial services. Moreover, access to the internet has contributed to inequality in the use of digital financial services. In terms of economic implications, countries with the lowest digital financial inclusion must revise their legal systems and invest in internet infrastructure.

1. Introduction

Financial inclusion, a common concept in scholarly literature, is defined as the “process that ensures the ease of access, availability, and use of the formal financial system for all members of an economy” (Sarma, 2008, p. 3). Garnering significant attention, this concept has been extensively explored in theoretical and empirical research. Since Kofi Annan’s call for inclusive finance, numerous theoretical works have emphasized the significance of inclusion based on the United Nations’ Millennium Development Goals framework. Access to financial services enables vulnerable groups to improve their living conditions, among other things. Several empirical research studies have reached the consensus that involving individuals in financial systems plays a significant role in alleviating poverty (Álvarez-Gamboa et al., 2021; Dogan et al., 2021; Erlando et al., 2020; Omar and Inaba, 2020; Park and

Merkado, 2015).

Microfinance has been widely acknowledged for its inclusivity due to its historical focus on serving marginalized groups excluded from conventional financial systems, which distinguishes it from traditional banking institutions. Researchers, particularly those in Asia, have sought to assess the significance of microfinance in promoting financial inclusion as it addresses the financial exclusion of impoverished individuals in certain regions or nations. This body of studies contributes to the empirical literature on financial inclusion. Since the World Bank’s Findex¹ database—which has been collecting data on access to and use of financial services in several countries since 2011—was released, there has been an increasing interest in financial inclusion. This database has also stimulated a large amount of research on financial inclusion. This topic interests poor as well as developed nations. Several central banks, notably those in developing nations, have implemented annual surveys

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* Corresponding author. Université de Rouen Normandie, Normandie Univ, LERN UR 4702, F-76000, Rouen, France.

E-mail addresses: christiankamenga@gmail.com, christian.kamenga@unhorizons.org (C. Kamenga Mapurita), celestin.mayoukou@univ-rouen.fr (C. Mayoukou).

¹ Financial inclusion index.

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to ascertain the extent of financial inclusion within their respective monetary regions. The subject under consideration pertains to the Central Bank of West African States.

Traditionally, most empirical studies determine financial inclusion using variables that provide information on the supply of financial services by conventional financial institutions, the demand for those services, or both. On the supply side, financial service penetration, defined by the number of bank branches or ATMs² per 100,000 inhabitants, is a common metric. On the demand side, the empirical literature lists variables related to access (the number of bank accounts per 100,000 inhabitants) and use (the respective quantity of loans and deposits as a percentage of the GDP). For a summary of these indicators, please refer to the works of Gupte et al. (2012), Caamara and Tuesta (2014), Pesqué-Cela et al. (2021), and Khera et al. (2022).

Technological advancements in the financial industry have paved the way for digital financial services (DFSs) and generated considerable interest among scholars and practitioners alike, leading to the formulation of a novel set of metrics related to access to and use of financial services. These metrics aim to enhance our comprehension of the advancements achieved in financial inclusion over the past decade. The GPMI (2016)³ conducted a review of the G20 financial inclusion indicators considering the digitalization of financial services, namely, remote transactions, digital payments, possession of a debit card, and access to digital infrastructure, among other factors (Tay et al., 2022, p. 5).

In the existing literature, including studies by Aslan et al. (2017), Huong Nguyen (2021), Shen et al. (2020), Huong Tram et al. (2023), and Al-Smadi (2023), these indicators are used to construct a comprehensive measure of financial inclusion. This measure encompasses both *traditional financial inclusion*, propelled by conventional financial institutions, and *digital financial inclusion* (DFI), enabled by new players such as *FinTech*⁴ and *telcos*.⁵ Thus, financial inclusion is holistically approached. Nevertheless, accurately assessing the extent to which digital technology contributes to global financial inclusion remains a challenge. In other words, the abovementioned studies could not disentangle the extent of inclusivity facilitated by traditional financial institutions and emerging digital players.

Recently developed dynamic general equilibrium models by Finkelstein and Mandelman (2021), replicated with some methodological differences by Kame Babilla (2023), distinguish traditional financial intermediation from digital financial intermediation, highlighting the importance of this issue. The lack of separation between existing and new financial service providers poses a barrier to effectively tracking progress in DFI. Therefore, the challenge lies in accurately comprehending advancements in DFI. This study primarily aims to propose a metric for measuring DFI.

Constructing this metric will facilitate the enhanced identification of gaps and barriers to inclusion. Addressing and surmounting these gaps and barriers effectively will ensure that the benefits of transformation and/or the digital revolution are equitably accessible to all individuals, particularly those who are vulnerable or have low income.

Our research is consistent with Khera et al.'s (2022) work. Using data from the Global Findex and Financial Access Survey, these authors created a DFI measure. Similarly, Mostafa Ismael & Metwally Ali (2021) developed an analogous metric using Egyptian data. Irrespective of its form, traditional or digital, financial inclusion is theoretically acknowledged as a multidimensional phenomenon, i.e., it can be measured based on various dimensions, including access to financial services, costs of accessing those services, and inherent barriers. The

huge challenge posed by the multidimensionality of financial inclusion is determining how many dimensions to retain in a study, how much weight to assign to each, and how to combine these dimensions into a single index (Kebede et al., 2021, p. 366).

The assessment framework provided by Khera et al. (2022) for measuring DFI in emerging and developing nations focuses exclusively on the variables of access and use.⁶ Drawing upon the research conducted by Caamara & Tuesta, 2014 and 2017, Khera et al. employed a two-step principal component analysis (PCA) technique to compute the weights assigned to each dimension of financial inclusion. Subsequently, these weighted dimensions were combined into a composite index, referred here to as the Khera et al. index. This index reveals a substantial increase in DFI from 2014 to 2017 for the countries included in their study. In contrast, traditional banking inclusion measures have either remained stagnant or regressed. However, this innovative outcome remains subject to two primary limitations:

- (i) The Khera et al. index fails to adequately account for the significance of financial operations, such as deposits made to a mobile account, mobile transfers between individuals, and the use of mobile money accounts for purchases, such as airtime or mobile data.
- (ii) The Khera et al. index does not incorporate regulatory constraints that affect the accessibility and use of DFSs. The quality of the digital infrastructure is a crucial factor to consider. Regrettably, this dimension is not considered when measuring financial inclusion (Tissot and Gadanez, 2017, p. 3). Nevertheless, this particular dimension comprises other components that facilitate financial system operations. According to Tissot and Gadanez (2017, p. 3), the “establishment of a robust, reliable, and effective information and communications technology infrastructure that is widely accessible plays a crucial role in facilitating the delivery of novel financial services and a variety of financial products.”

This study addresses these gaps. This article proposes a measure for DFI that combines (i) the significance of financial transactions and (ii) the quality of digital infrastructure. This metric is termed the digital financial inclusion index (DFII).

The novelty of this study lies in its development of a DFII tailored for nations in sub-Saharan Africa (SSA). The African continent experiences a higher degree of DFI compared with other global regions. Based on the 2021 Global Findex database, it is evident that the level of mobile phone-based financial service inclusion is three times greater in SSA compared with other regions. Furthermore, these data emphasize that the proportion of individuals with access to these novel services surpasses that of individuals with access to a financial institution in the same region of Africa. This database moreover indicates a significant increase in the number of mobile accounts in various economies in the region between 2014 and 2021. In contrast, the number of accounts held with financial institutions has exhibited a contrasting pattern, as highlighted by Demirgüç-Kunt et al. (2022, p. 20). An illustrative case in this domain is that of Zambia. According to Demirgüç-Kunt et al. (2022, p. 20), the number of bank accounts in the country decreased by 12% between 2017 and 2021, dropping from 36% to 24%. In contrast, mobile accounts significantly increased by approximately 14%, rising from 28% to 42%. The use of DFSs increased after various countries implemented containment measures and social distancing protocols in response to the global COVID-19 pandemic in 2020 and 2021. During this health crisis, there was a notable surge in remote payments, with a substantial increase from 34% to 57% in SSA between 2014 and 2021.

Despite advancements in the development of DFSs in this region of Africa, no comprehensive measure is currently available to quantify this progress. Measuring progress in DFI also holds particular importance for

² Self-service banking (ATM: automated teller machines).

³ Global Partnership for Financial Inclusion.

⁴ These are start-ups that link technology with finance to offer digital financial services.

⁵ Telecommunications firms.

⁶ To these two dimensions, Ismael and Salah Ali (2022) have added a third: the barrier inherent in access to financial services.

the SSA region because several African countries “have recently witnessed conflicts and turmoil resulting from high unemployment, income erosion, and marginalization of a large segment of the population” (Al-Smadi 2023, p. 465). Moreover, the extent to which COVID-19 affects DFI has not received sufficient attention in prior literature. Consequently, this paper seeks to respond to the following questions:

- (1) What is the overall level of DFI in SSA countries from 2014 to 2021?
- (2) How did COVID-19 affect DFI in the SSA region from 2020 to 2021?
- (3) Have SSA countries gained equally from the digital financial revolution? If not, what explains the disparities in DFI among these countries?

To the best of our knowledge, this is the first study on this issue covering the SSA region. This study contributes to the emerging literature on financial inclusion in several ways. It presents a comprehensive measurement of DFI from 2014 to 2021. Using the latest data provided by the Global Findex, this research contributes to the literature on the effects of the COVID-19 pandemic on DFI. In the spirit of Aslan et al. (2017), the final contribution of this article is to suggest a Shapley decomposition analysis (Shorrocks, 1999) to explain the variations in DFI levels among the nations examined. This study adds to the existing literature investigating disparities or inequalities in financial inclusion by examining the factors that lead to inequality in access to and use of DFSs.

The remainder of the article is structured as follows. Section 2 reviews the literature on measuring financial inclusion. Section 3 presents the construction of the data and the research methodology. Section 4 emphasizes and discusses the results obtained. Section 5 concludes the paper.

2. Literature review

2.1. Theoretical approaches to developing a composite indicator

The literature employs two methodologies for developing a composite indicator of financial inclusion, as discussed by Huong Nguyen (2021, p.80) and Huong Tram et al. (2023, p.223): nonparametric and parametric methods. The initial step involves assigning a specific weight to each dimension of financial inclusion. This assignment relies upon the researcher's combination of intuitive knowledge and subject-specific information. Sarma's (2008) paper, widely recognized as groundbreaking in the field of financial inclusion measurement, aligns with this approach. She assigned equal unity weights to the three dimensions of financial inclusion, specifically penetration, availability, and use. Continuing her research, Sarma and Pais (2011) assigned identical weights (0.5) to both availability and use variables. However, they hold the weight of unity for the penetration variable, as in Sarma's work. The Euclidean distance methodology was used to compute the composite index. The change in the weighting of the financial inclusion dimensions between the initial and subsequent publications reflects what might be described as the “arbitrary” nature of nonparametric methods. Lockwood (2004) stated that this change can significantly impact the outcomes of the composite index (as cited in Huong Nguyen, 2021, p.80). Parametric approaches are more extensively employed due to this rationale. This type of approaches benefits from adjusting the weights assigned to the various dimensions of financial inclusion per the data structure. In alternative terms, the determination of weights is endogenous, which distinguishes it from nonparametric approaches wherein the weights are exogenously set. PCA is one such technique that employs orthogonal rotation to reduce the number of variables with significant loadings on each factor (latent factor or factor axis). The weight to be retained is determined based on the correlation between the variable and the factorial axis. Caamara and Tuesta (2014) were the first to

employ PCA method to create a composite financial inclusion index in developed and developing nations. It was subsequently discussed in works by Huong Nguyen (2021), Le et al. (2020), Khera et al. (2022), Chuc et al. (2022), and Wang and Luo (2022). Likewise, this article adopts this approach. Other authors have used entropy methods (Dong et al., 2022) or factor analysis (Amidžić et al., 2014) in conjunction with unsupervised methods (Kebede et al., 2021). PCA was chosen because it overcomes the shortcomings of the Khera et al. index,⁷ without getting bogged down in considerations of methodological choice within the parametric family of methods.

By constructing a composite index, factors that explain financial inclusion can be identified (Kebede et al., 2021; Kishore and Singh, 2019) and a country or region's level of financial services development over time in relation to other countries or regions can be determined. Such an index can also be used to assess the effect of financial inclusion on a particular variable. In this context, the literature employs the composite index to better evaluate the impact of financial inclusion on macroeconomic variables—such as economic development (Kishore and Singh, 2019; Sarma and Pais, 2011), financial stability (Vo et al., 2021; Wang and Luo, 2022), income inequality (Sawadogo and Semedo, 2021), monetary poverty (Gutiérrez-Romero and Ahamed, 2021; Lee et al., 2023), and climate change (Dong et al., 2022; Le et al., 2020; Renzhi and Jun, 2020)—or microeconomic variables such as multidimensional poverty (Álvarez-Gamboa et al., 2021), bank profitability (Kumar et al., 2020), and mental health (Ajefu et al., 2020). Other studies, such as the one by Chuc et al. (2022), used the composite index as an intermediation variable to gauge the impact of cash transfers on economic growth. Within the scope of this article, the development of the composite index also makes it possible to capture the effects of the COVID-19 pandemic on DFI.

2.2. Impact of COVID-19 on digital financial inclusion

In contrast to the financial crisis—which can be attributed in part to financial innovation and which subsequently led to increased caution among economic agents regarding the use of novel financial instruments—the ongoing health crisis caused by the COVID-19 pandemic has paradoxically stimulated the use of modern financial services, namely, remote payment means. International Monetary Fund (IMF) analysts argue that “lockdowns and social distancing are accelerating the use of DFSs, just as the 2003 SARS epidemic hastened China's launching of digital payments and e-commerce”.⁸ The World Bank also agrees, stating that “when COVID-19 hit, governments rushed to provide financial relief to citizens, often using digital channels to do so. At the same time, social distancing forced people to find alternatives to cash and face-to-face shopping. These shifts fueled speculation that the pandemic would create an overall rise in digital financial inclusion”.⁹ Certain polls, particularly those conducted by Global Findex in 2021, provide evidence supporting these claims. Based on the data provided, there was a notable increase in the percentage of adults (aged ≥15 years) engaging in digital payments in developing nations, rising from 35% in 2014 to 57% in 2021. Additionally, a significant portion of individuals—over one-third—reported initiating commercial bill payments through mobile devices for the first time during the COVID-19 pandemic.

By emphasizing the potential advantages associated with the growth of DFSs in both the pre- and post-pandemic eras, Agur et al. (2020) posits that DFSs or mobile financial services can be perceived as a reaction to the adverse consequences of the health crisis, thereby potentially

⁷ By reproducing their methodology.

⁸ <https://www.imf.org/en/Blogs/Articles/2020/07/01/blog-digital-financial-inclusion-in-the-times-of-COVID-19>, accessed on March 22, 2023, at 3:15 p.m.

⁹ <https://blogs.worldbank.org/latinamerica/rise-digital-financial-inclusion-during-covid-19-pandemic>, accessed on March 21, 2023, at 10:51 a.m.

expediting the advancement and adoption of these digital services due to their advantages.

Klapper and Miller (2021) underscored the influence of the COVID-19 pandemic on the uptake of DFSs in their report submitted on behalf of GPFI. In addition to the constraints surrounding the implementation of digital tools and strategies for promoting the use of DFSs, the study examined the impact of digital payments on measures undertaken to address the pandemic, specifically in terms of containment and social distancing. Drawing on the data published by the World Bank and other institutions, they concluded that digital payments were extensively implemented as a response to the health crisis, resulting in a notable advancement in DFI. Nevertheless, the researchers observed patterns indicating disparities in the availability of DFSs among vulnerable populations.

Based on empirical evidence and current understanding, the examination of the effects of the COVID-19 pandemic on DFI has been limited to the scholarly contributions of Fu and Mishra (2022) and Sugandi (2021). The former studied the impact of the health crisis on the adoption of digital finance. Based on a representative sample of several nations, the findings of Fu and Mishra (2022) indicate a rise in the adoption rate of digital financial apps, ranging from 21% to 26% during the health crisis. This observation implies the potential for an upsurge in DFI. Sugandi (2021) investigated the impact of the COVID-19 pandemic on FinTech's activities in Indonesia. Their findings challenge the assumption that the pandemic directly impacts transaction values through mobile money, mobile banking, internet banking, and e-money. Consequently, the researcher concludes that the health crisis did not expedite the provision of payment and lending services by FinTech companies. These arguments fail to provide evidence for a tangible rise in DFI after the COVID-19 pandemic. While these studies offer a basis for modeling, it is essential to acknowledge a significant constraint in the modeling methodology. The issue of DFI is currently addressed in a limited manner, with a focus on a single aspect, namely, access to mobile finance applications or FinTech activities. However, a more comprehensive approach might be adopted by considering multiple dimensions and synthesizing them using a composite indicator.

3. Data and methodologies

The data and methodologies used are described below.

3.1. Data and attribute descriptions

The data used in this study were obtained from various publications, including those of the World Bank, Global Findex, IMF Financial Access Survey, Network Index Readiness, and International Telecommunication Union. The study encompasses a total of 14 nations¹⁰ over three time periods: 2014, 2017, and 2021. The study primarily aims to examine DFI through the lens of three key dimensions: access to financial services, the use of such services, and the quality of the services provided. Access refers to the level of convenience associated with using financial services and goods supplied by emerging digital players, as well as physical proximity to mobile service points. In certain research endeavors, the metric used to assess DFI is the percentage of individuals possessing a mobile money account. Nevertheless, this metric lacks relevance for comprehensively understanding the extent of DFI as accounts may be active or dormant. The type of account a user has depends upon how frequently they conduct financial transactions using cellular devices. Inactive accounts conduct few or no transactions. Operational

¹⁰ These countries are selected according to the availability of data on the quality of financial services. The list includes Burkina Faso, Cameroon, Côte d'Ivoire, Ghana, Guinea, Kenya, Malawi, Mali, Nigeria, Senegal, Tanzania, Uganda, Zambia, and Zimbabwe. Mozambique was also part of this sample. It was removed as its observations were classified as outliers.

Table 1

Description of digital financial inclusion dimensions and data sources.

Dimensions	Attributes	Code	Source
Access	Proportion of adult population with access to the internet	K ₁	International Telecommunication Union
	Number of broadband cable subscriptions	K ₂	World Bank
	Number of mobile phone subscriptions	K ₃	World Bank
	Number of mobile money agents within a radius of 1000 km squared	K ₄	Financial Access Survey
Use	Proportion of adult population with a mobile money account	L ₁	Global Findex
	Volume of transactions using mobile money per 1000 adults	L ₂	Financial Access Survey
	Proportion of the adult population who receive salaries through mobile money	L ₃	Global Findex
	Proportion of adult population that pays commercial bills using mobile money	L ₄	Global Findex
	Proportion of adult population that makes purchases online	L ₅	Global Findex
Quality	ICT regulations	M ₁	Network Index Readiness reports
	Internet server security	M ₂	World Bank

ICT: information communication technology

Source: Authors' compilation based on various sources

accounts conduct transactions regularly. Using DFSs is a significant aspect within the realm of DFI. This use encompasses the regularity and depth of use of DFSs and digital financial products. Regulatory constraints also impact access to and use of DFSs. The extent to which individuals can trust these emerging services is closely associated with the extent of security measures implemented by these services. Hence, consumer protection is a pivotal aspect in the policies of DFS providers. The quality of the digital infrastructure is reflected in providers' security measures. The third dimension has been incorporated to quantify the extent of DFI, building upon the existing two dimensions.

Table 1 provides an overview of the attributes associated with the three dimensions of DFI and the corresponding data sources. We used the expectancy maximum likelihood¹¹ method to impute values for missing observations (Little, 1988). Prior to implementing this approach, we addressed missing data by using scholarly and report publications that encompassed the selected countries in our sample

3.2. Analytical framework for composite index construction

To apply PCA, two conditions must be met: (i) the presence of correlation among attributes and (ii) data factorization. The acceptance of correlation between attributes is contingent upon the correlation coefficients reaching a minimum threshold of 0.30. Factoring verification is conducted using statistical methods such as the Kaiser–Meyer–Olkin (KMO) test for sampling adequacy and Bartlett's sphericity test. According to Dziuban and Shirkey (1974, p. 359), sampling adequacy is better when the KMO coefficient is in the 0.8–1.0 range, satisfactory in the 0.7–0.79 range, and acceptable in the 0.5–0.69 range. PCA cannot be used when the value falls below the threshold of 0.5. Bartlett's sphericity test is employed to evaluate the null hypothesis (H0) of independence against the alternative hypothesis (H1) of dependency between the indicators used for assessing a latent variable. The rejection of the null hypothesis indicates that the correlation matrix is appropriate for PCA owing to interdependence among the indicators measuring the latent variable.

¹¹ Details on the choice of this technique are available upon request.

If the aforementioned conditions are confirmed, PCA can be employed. According to Caamara and Tuesta (2014, 2017), PCA can be performed in two-steps. In the initial stage, PCA is applied to each dimension of DFI to generate subindices by considering the weights assigned to each attribute. The second stage involves the application of PCA to the subindices generated in the previous step. The composite DFII is constructed based on the relative weights assigned to each subindex.

3.2.1. PCA stage 1

This stage involves estimating the dimensions of DFI. These variables are endogenous and lack direct measurability.¹² We designate access, use, and quality of financial services by $(A)_{it}$, $(U)_{it}$, and $(Q)_{it}$,¹³ respectively, for country i at time t .

$$(A)_{it} = \rho_1(\text{Log } K_1)_{it} + \rho_2(\text{Log } K_2)_{it} + \rho_3(\text{Log } K_3)_{it} + \rho_4(\text{Log } K_4)_{it} + \mu_{it} \quad (1)$$

$$(U)_{it} = \tau_1(\text{Log } L_1)_{it} + \tau_2(\text{Log } L_2)_{it} + \tau_3(\text{Log } L_3)_{it} + \tau_4(\text{Log } L_4)_{it} + \tau_5(\text{Log } L_5)_{it} + \omega_{it} \quad (2)$$

$$(Q)_{it} = \pi_1(\text{Log } M_1)_{it} + \pi_2(\text{Log } M_2)_{it} + \alpha_{it}. \quad (3)$$

The logarithm of each attribute's modality in the three dimensions of DFI is considered in the given equations. Here, μ_{it} , ω_{it} , and α_{it} are error terms. The parameters ρ , π , and τ are unknown and can be estimated simultaneously for the three dimensions, which also serve as indices, using PCA as a method for linearly combining the attributes. Thus, Equations (1)–(3) are expressed differently from the k th principal component, denoted as $P_k = X\lambda_j$, where $k = 1, \dots, p$; X is the attributes matrix; and $\lambda_j (j = 1, \dots, p)$ is the j th eigenvalue. It designates the number of principal components and corresponds to the number of attributes of each dimension. These equations are equivalent respectively to

$$(A)_{it} = \frac{\sum_{j,k=1}^p \lambda_j^A P_{kit}^A}{\sum_{j=1}^p \lambda_j^A}. \quad (4)$$

$$(U)_{it} = \frac{\sum_{j,k=1}^p \lambda_j^U P_{kit}^U}{\sum_{j=1}^p \lambda_j^U}. \quad (5)$$

$$(Q)_{it} = \frac{\sum_{j,k=1}^p \lambda_j^Q P_{kit}^Q}{\sum_{j=1}^p \lambda_j^Q}. \quad (6)$$

Given the ordering of eigenvalues ($\lambda_1 > \lambda_2 > \dots > \lambda_p$), the weights assigned to each principal component exhibit a decreasing pattern. This implies that the first principal component accounts for a significant portion of the variance, whereas the second principal component explains a comparatively smaller proportion, and so forth. In general, the analysis often retains either the first component or the first two components based on the proportion of total variance explained. This selection adheres to the eigenvalue criteria by retaining components with eigenvalues greater than one. However, this phenomenon results in the neglect of other components that appear to have minimal impact. Following the methodology proposed by Caamara & Tuesta (2014, 2017), we included all components in our analysis to ensure that we captured 100% of the total variance of the model.

3.2.2. PCA stage 2

The subsequent stage involves implementing PCA on the subindices derived from the preceding step. Let ϕ_1 , ϕ_2 and ϕ_3 the weights correspond to relative contributions of access, use, and quality variables,

respectively, using PCA. The composite DFII $(DFII)_{it}$ is a weighted average of these three subindices. It is given by

$$(DFII)_{it} = \phi_1(A)_{it} + \phi_2(U)_{it} + \phi_3(Q)_{it} + \xi_{it}. \quad (7)$$

with ξ_{it} as the error term.

3.3. COVID-19 and digital financial inclusion

This work adopts a modeling approach to investigate the impact of the COVID-19 pandemic on DFI. It builds upon prior research conducted by Fu and Mishra (2022) and Sugandi (2021). The control variables are based on the financial inclusion literature (Rojas-Suárez, 2016; Rojas-Suárez and Amado, 2014). Following Khera et al. (2021), we also included variables capturing the banking level (use of traditional financial services). The model used is delineated as follows:

$$\begin{aligned} \text{Log } (DFII)_{it} = & a_1 + a_2(\text{Covid})_{it} + a_3 \text{Log } (GDP)_{it} + a_4 \text{Log } (\text{BankConc})_{it} \\ & + a_5 \text{Log } (\text{BankOv})_{it} + a_6 \text{Log } (RL)_{it} + a_7 \text{Log } (Ur_pop)_{it} \\ & + a_8 \text{Log } (FI_account)_{it} + a_9 \text{Log } (Deb_Card)_{it} + \zeta_{it}. \end{aligned} \quad (8)$$

With Covid	:	is a dichotomous variable that provides information on COVID-19. It is set to 1 in 2021 and 0 otherwise.
Log(GDP)	:	refers to the logarithm of growth domestic product per capita (source: World Bank Development Indicator).
Log(BankConc)	:	refers to the logarithm of bank concentration. This variable reflects a share of assets of three largest commercial banks to total commercial banking assets. This is an indicator of the financial sector inefficiency. (source: World Bank Finstat).
Log(BankOv)	:	refers to the logarithm of Bank overhead cost to assets. It reflects as the previous variable the banking inefficiency indicator (data source: World Bank Finstat).
Log(RL)	:	refers to the logarithm of the rule of law. It is a proxy capturing the perception of confidence in the rules of the society and reflects the quality of institutions. Its values are comprised between 0 (lowest rule of law) and 1 (strongest rule of law) (data source: World Justice Project).
Log(Ur_pop)	:	refers to the logarithm of share of urban population (source: World Bank Development Indicator).
Log(FI_account) _{it}	:	refers to the logarithm of Financial account—the percentage of adult aged 15 and above who report having an account at a bank or another type of financial institution (source: Global Findex).
Log(Deb_Card) _{it}	:	refers to the logarithm of debit card - the percentage of adult aged 15 and above who report having a debit card (source: Global Findex).
ζ_{it}	:	denotes the error term.

According to the literature on growth and finance, Equation (8) contains endogenous bias. GDP affects DFII and DFII also affects GDP.¹⁴ In the econometric literature, this is called the “simultaneity bias.” The econometric tradition recommends replacing the endogenous variable with a suitable instrument to address the endogeneity issue. In theory, the instrumental variable (IV) must satisfy the relevance condition by being correlated with the endogenous variable, and it must also satisfy the orthogonality or exogeneity condition by not being correlated with the error. In addition, the IV should not directly affect the dependent variable. Another condition related to the IVs is their strength, i.e., the IV should be strong. The consequences of weak instruments are widely

¹² We are talking about latent variables here.

¹³ The data are taken as logarithms to reduce the dispersion around their average value and mitigate the effects of potential “aberrant” observations.

¹⁴ We acknowledge the anonymous reviewers for their helpful comments.

discussed and documented in the econometric literature.

We used the logarithm of electricity access as an IV based on intuition. Ritchie et al. (2019) have shown that energy access is low in economically disadvantaged countries and improves as income levels rise. This outcome aligns with the “conservation hypothesis,” which asserts that economic expansion drives the development of the energy industry (Economic Consulting Associates, 2014). Furthermore, access to electricity does not directly affect DFI; however, it is a prerequisite for using digital means to achieve DFI.

The relationship between GDP and access to electricity (*accele*)¹⁵ can be expressed as follows:

$$\begin{aligned} \text{Log}(\overline{\text{GDP}})_{it} = & b_1 + b_2(\text{accele})_{it} + b_3 \text{Log}(\text{Covid})_{it} + b_4 \text{Log}(\text{BankConc})_{it} \\ & + b_5 \text{Log}(\text{BankOv})_{it} + b_6 \text{Log}(\text{RL})_{it} + b_7 \text{Log}(\text{Ur.pop})_{it} + b_8 \text{Log}(\text{FI_account})_{it} + b_9 \text{Log}(\text{Deb_Card})_{it} + \pi_{it}. \end{aligned} \quad (9)$$

4. Results and discussions

4.1. Trends in digital financial inclusion indicators

The data presented in Figs. 1–3 demonstrate a substantial growth in the accessibility of DFSs in all examined nations from 2014 to 2021. In 2021, Ghana, Nigeria, and Senegal show comparatively elevated internet access rates (Fig. 1). Uganda’s internet accessibility exhibited no improvement from 2014 to 2021. Both Kenya and Tanzania have a significant degree of broadband cable subscription, whereas Burkina Faso and Malawi have not significantly advanced in this domain (Fig. 2). Between 2017 and 2021, the rate of mobile phone subscription in nearly one-third of the examined countries, which include Côte d’Ivoire, Ghana, Mali, Senegal, and Kenya, surpassed 100% (Fig. 3). Among the countries whose ownership rate exceeds 100%, Mali shows downward trajectory potentially because of the prevailing instability resulting from violent internal conflicts. Côte d’Ivoire was the foremost nation with a mobile phone ownership rate of more than 150% in the year 2021. Conversely, Malawi had the lowest mobile phone ownership rate between 2014 and 2021. Regarding the adoption of DFSs, there has been a remarkable increase in the concentration of mobile money agents per 1000 square kilometers in more than 50% of the examined nations during the study period. In 2021, Ghana, Senegal, and Uganda exhibited the highest concentration of mobile hotspots within a geographical area spanning 1000 square kilometers (Fig. 4).

Figs. 5–9 illustrate significant upward trends in the proportions of adult populations who possess a mobile account (Fig. 5), make transactions using a mobile money account (Fig. 6), receive their paycheck through a mobile money account (Fig. 7), use their mobile phones for making payments (Fig. 8), and make purchases online (Fig. 9). These trends are observed from 2014 to 2021. The figures mentioned above underscore the significance of using financial services and the magnitude of transactions conducted via “mobile money.” Kenya exhibits the most pronounced use of DFSs among all nations. Furthermore, considering the magnitude of transaction volumes facilitated by mobile money, it appears that Uganda and Ghana display the most substantial transaction volumes in 2021. The significant level of service use in Kenya can be attributed to the country’s pioneering launch of this

service in Africa in 2007, facilitated by Safaricom, a subsidiary of Vodafone operating within the country. A dilemma arises in the context of Nigeria, which has the lowest use rate of DFSs. Additionally, this nation has the lowest proportion of the adult population possessing a mobile account in the year 2021. In 2014, Nigeria demonstrated a significant prevalence of online platforms for transactions and payments. However, it is essential to acknowledge a decrease in online payment transactions from 2017 to 2021.

Quality of financial services shows a trend that is similar to those of accessibility and use of financial services, as depicted in Figs. 10 and 11, spanning 2014 to 2021. This development is indicative of the regulatory

initiatives implemented in numerous nations to enhance the regulation of emerging technology. Achieving internet server security for a population of one million is challenging. As of 2021, Kenya and Nigeria were the only countries to provide security to a population of more than 10, 000, 000 individuals, as shown in Fig. 11. Furthermore, in 2014, the above statistics showed a threefold increase in the case of Nigeria. The decrease in the proportion of adults in this country who used online payment methods between 2014 and 2021 may be associated with a fall in the extent of internet server security coverage among the population.

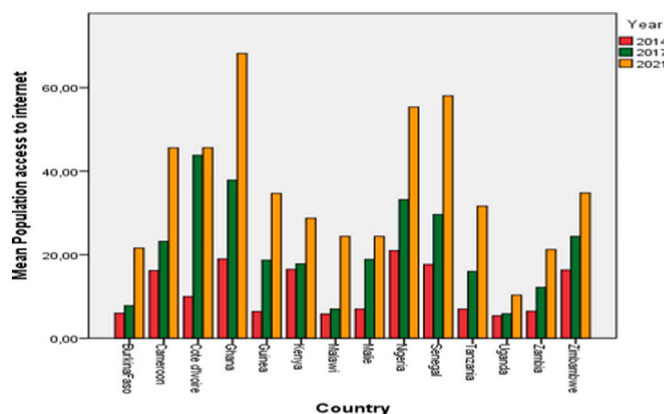


Fig. 1. Evolution of internet access among the population by country between 2014 and 2017.

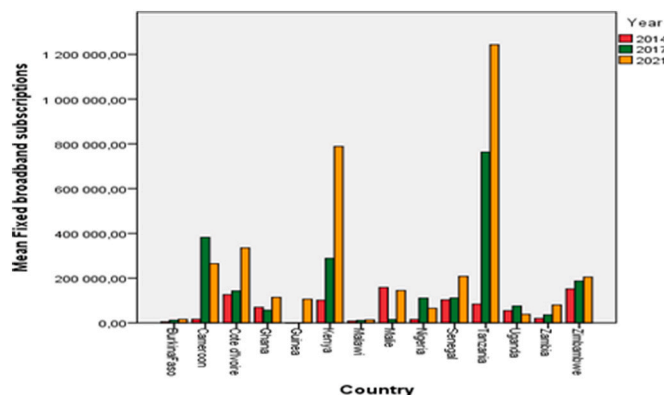


Fig. 2. Evolution of high-speed cable subscriptions per country between 2014 and 2017.

¹⁵ The relationship between logarithm of GDP and Log of access to electricity is very strong and highly significant as indicated by the correlation coefficient ($r = 0.81^{***}$).

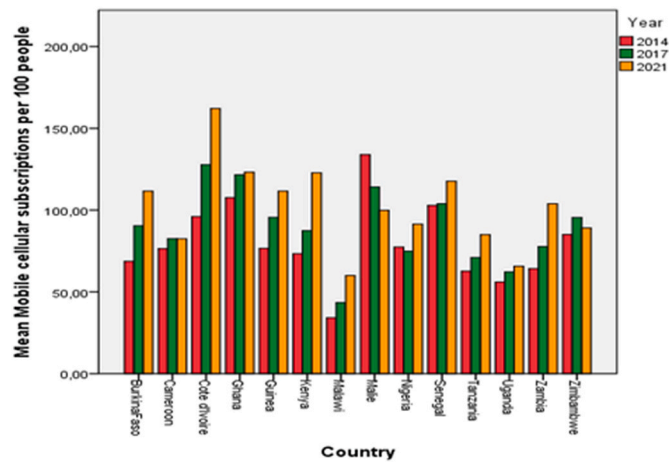


Fig. 3. Evolution of mobile phone subscriptions by country in 2014 and 2017.

Based on the observed advancements in the accessibility, use, and quality of DFSs, we anticipate a positive trajectory in the DFII from 2014 to 2021.

4.2. Data correlation and factorization tests

The correlation matrix between the attributes of each dimension selected for measuring DFI is presented in the Appendix (See Table A1). From the access perspective, there is a significant and positive correlation between each attribute, except for the logarithm of the number of agents registered with the mobile money service (LogK4), which exhibits a weak correlation coefficient of 0.18 and lacks statistical significance, as well as the logarithm of mobile phone subscription (LogK3). In general, excluding the LogK4 attribute from the analysis is advisable. However, considering its significance in facilitating the advancement of DFSs, we choose to retain it. Regarding use, robust positive and statistically significant connections are observed among various attributes. Regarding quality, a notable and statistically significant relationship exists between the logarithm of information communication technology (ICT)-related regulation (LogM1) and internet server security (LogM2).

The correlations between the attributes of each dimension of DFI are necessary conditions for implementing PCA. The sufficient condition is that of the factorization of the data. The KMO coefficients and Bartlett statistics are populated at the bottom of each matrix (see Table A1 in the Appendix) for each DFI subdimension. Sampling adequacy is significantly better for access (0.67) and use (0.78) than for quality, evaluated at 0.50 (corresponds to the minimum tolerance threshold (0.50)). Based

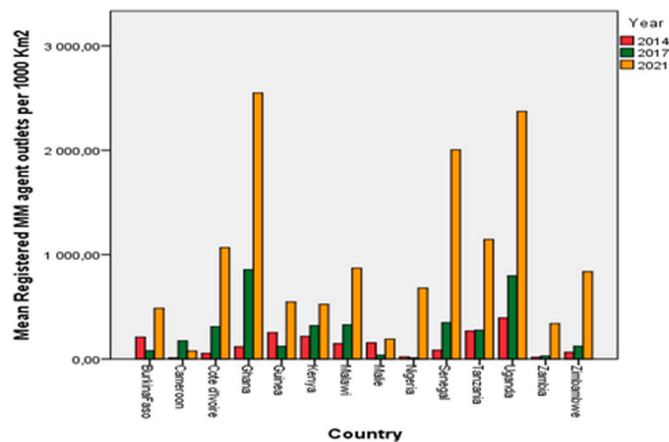


Fig. 4. Evolution of the number of mobile money agents per 1000 square kilometers between 2014 and 2017, by country.

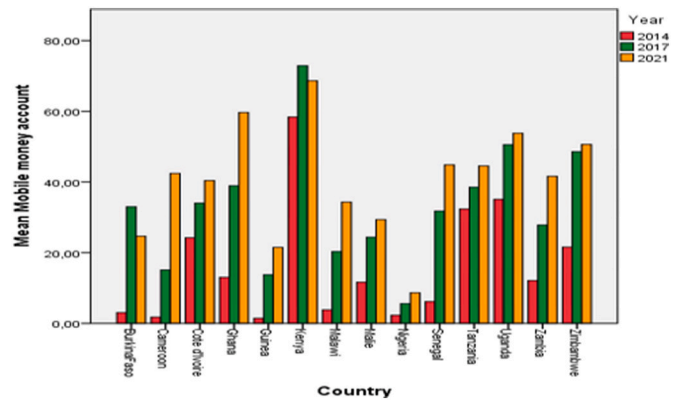


Fig. 5. Evolution of the proportion of the adult population holding a mobile money account between 2014 and 2017, by country.

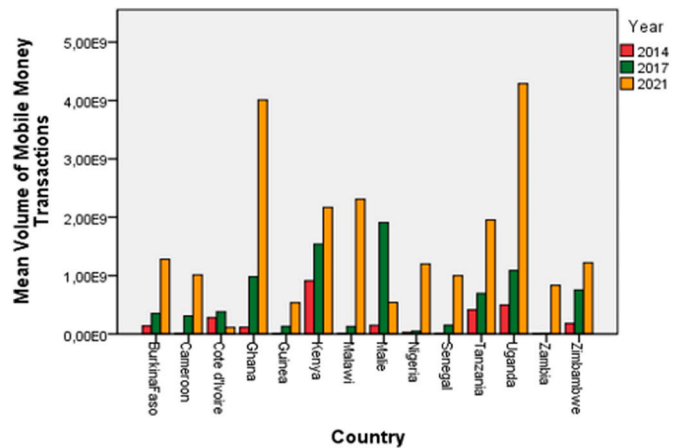


Fig. 6. Evolution of mobile money transaction volume per country between 2014 and 2017.

on the significance of Bartlett's chi-square statistics at the 1% confidence level, we deduce that the attributes that represent each subdimension of DFI are not independent of each other. Thus, the correlation matrices are ready for PCA.

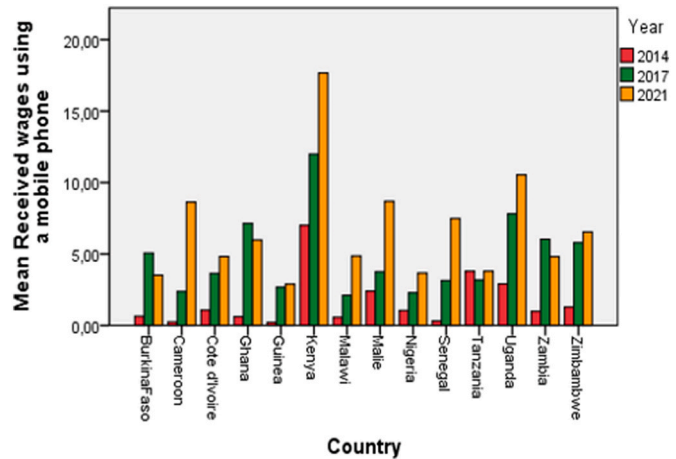


Fig. 7. Evolution of the proportion of the adult population receiving salary via mobile phone between 2014 and 2017 by country.

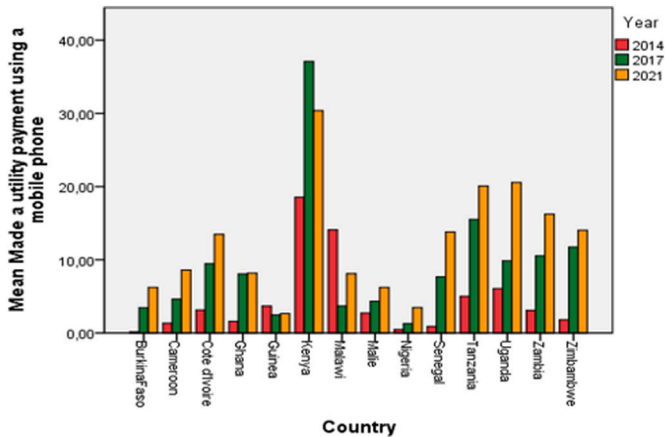


Fig. 8. Evolution of the proportion of the adult population making payments by mobile phone between 2014 and 2017 by country.

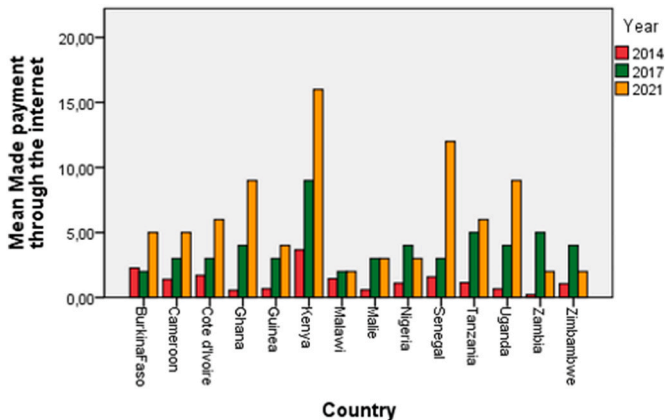


Fig. 9. Evolution of the proportion of the adult population engaging in online payments between 2014 and 2017 by country.

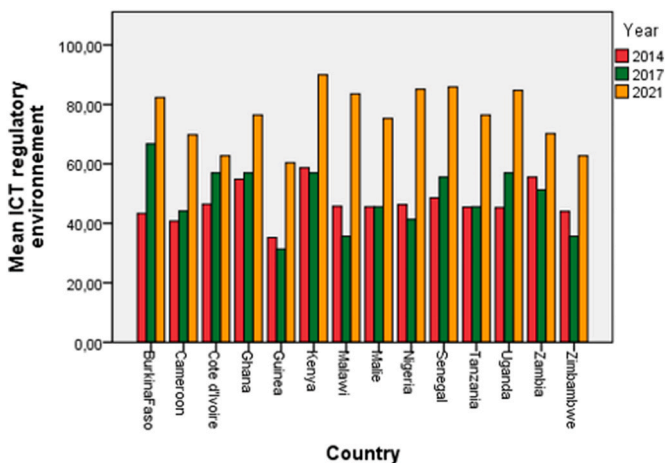


Fig. 10. Evolution of ICT regulatory quality between 2014 and 2017 by country.

4.3. Digital financial inclusion subindices

Weights for each attribute of the dimensions or subindices of DFI (namely, access, use, and quality) have been computed using Equations (1)–(3). The weights in Fig. 12 are normalized to ensure that their sum is

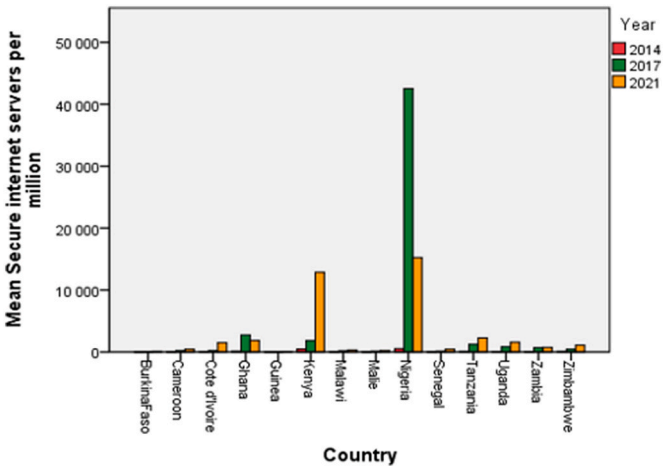


Fig. 11. Evolution of the number of individuals covered by internet server security between 2014 and 2017, by country.

equal to unity. With regard to access, mobile phone subscription carries the greatest significance, with a weight of 0.39. The findings suggest that several African nations have achieved a mature level of mobile network coverage that may be considered adequately developed. The weights for internet access (0.23) and broadband cable subscription (0.23) are evenly distributed. The density of mobile money agents has the lowest weight (0.15). The abovementioned four attributes are depicted on a factorial axis (see Table A2 in the Appendix). The first axis pertains to the mobile phone subscription, the second to subscriptions to broadband cable services, the third to the density of mobile money agents, and the fourth to access to the internet. Furthermore, these four attributes and their corresponding factorial axes have a strong, positive correlation, implying that the level of access to DFSs can be increased through attribute progression and decreased through attribute regression. Mobile phone subscription emerges as the primary access attribute, accounting for a substantial proportion (53.74%) of the total variance in the analytical model. It plays a significant role in facilitating widespread accessibility to DFSs. The substantial amount of variance accounted for by the principal axis also supports the notion that these four attributes indicate the same underlying phenomena. The contribution of internet access is insignificant, accounting for only 8.65% of the total variance, compared with the more substantial influence of broadband cable subscription (21.67%) and density of mobile money agents (15.92%). As a result, the accessibility of DFSs is lower than that of non-internet technologies. Nevertheless, the widespread implementation of access points for offline financial services has not been achieved to a significant extent, namely, in terms of covering an area of 1000 square kilometers,

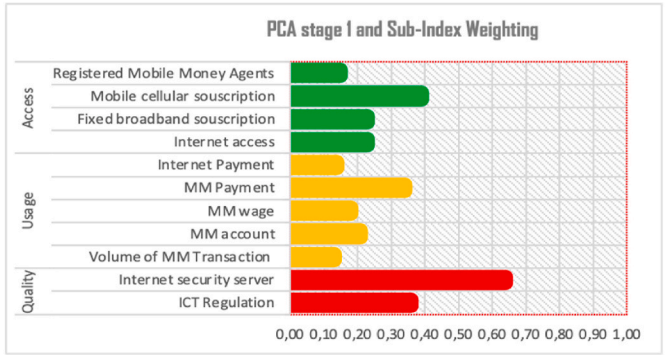


Fig. 12. MM: mobile money Attribute weights at PCA stage 1.

as indicated by the proportion of variance explained by the density of mobile money agents.

Regarding usage, the greatest weight is assigned to payment by mobile account (0.34), followed by ownership of mobile money accounts (0.21) and salary disbursements through mobile accounts (0.18). Internet payments and mobile account transactions are ranked at the lowest end of the spectrum, with scores of 0.14 and 0.13, respectively. The first axis, responsible for 75% of the model's overall variance, is most accurately characterized by the use of mobile account payment. Thus, this attribute comprehensively explains usage. A growing number of transactions, including phone credit, mobile data, bill payments, and cable TV subscriptions, are being conducted with mobile money accounts. This trend can be attributed to the numerous benefits associated with mobile money, including its enhanced accessibility and cost-effectiveness. The prevailing market position of mobile payment services is evidence of the advancement toward the dematerialization of payment means. The amount of mobile transactions characterizes the second factorial axis and accounts for 12% of the total variance in the model. This attribute is fundamental to providing services that have facilitated the extensive acceptance and diffusion of "mobile money." Moreover, the platforms of mobile transactions provide an alternative to internet-based money transfer services, which have been dominated by major corporations such as Western Union and Money Gram, resulting in a monopolistic market structure and imposing substantial transaction fees on its clients. The third factorial axis, internet payments, explains 9% of the total variance in the model. This indicates that the adoption of online financial services is progressively increasing, while it has not yet fully penetrated user behaviors satisfactorily. The final two factorial axes, representing the payment of salaries via mobile money accounts and the possession of mobile money accounts, exhibit a marginal contribution of 5%. Therefore, the explanation of usage by these attributes is relatively weak. In the initial scenario, specifically referring to the disbursement of salaries through mobile money accounts, it is evident that cash payment of wages remains the prevailing method in numerous SSA. In the second scenario about mobile account ownership, this outcome appears to contradict expectations. One conceivable rationale is that a specific demographic of individuals engage in mobile money transactions without possessing a formal account or even a mobile device. Individuals use the mobile account number, commonly called the phone number, belonging to their close relatives. This phenomenon which aligns with the social ties theory is not insignificant in the context of SSA.

When considering quality, it may be argued that internet server security (0.64) holds greater significance than ICT regulation (0.36). The first factorial axis indicates the variable under consideration and explains approximately 75% of the overall variance in the model. ICT regulation, which is linked to the second dimension, comprises the remaining 25%.

Subindices were created for DFSs access, use, and quality, considering the relative weights assigned to each category. The values have been standardized within the range of 0–1. The closer the values are to a unit, the higher is the degree of DFI; conversely, the closer they are to zero, the lower the degree of inclusion. The countries have been positioned in the space based on their respective levels of access, use, and quality of DFSs, as depicted in Figs. 15, 16, and 17. This projection aims to identify the specific areas in which a certain country exhibits a limited level of financial inclusion. This information is intended to assist policymakers in implementing appropriate measures to address these issues (Caamara & Tuesta, 2014, p.18).

4.4. Composite digital financial inclusion index

The subsequent stage involves the application of PCA on the subindices derived in the preceding step. The requirements of PCA application are verified using the data provided in Table A3 in the Appendix. We have shown the results of PCA (Table A4) and the normalized

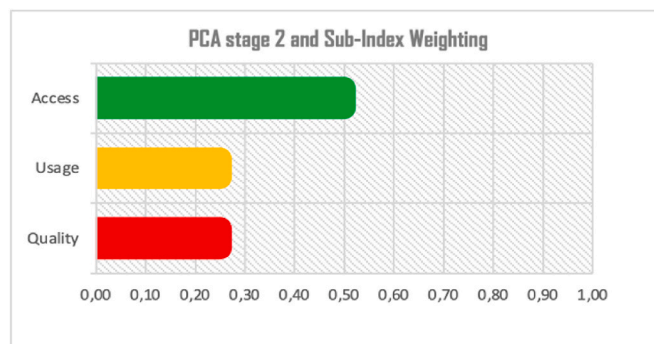


Fig. 13. Subindex weights at stage 2.

weights of each index (Fig. 13).

The access dimension carries the greatest weight, with a value of 0.50. The weights assigned to use and quality are equal, with each dimension having a weight of 0.25. Thus, access emerges as one of the most critical dimensions in explaining the degree of DFI. This result corresponds with the results of Caamara and Tuesta (2014), who demonstrated that access to banking services (weight of 0.42) is a significant attribute of traditional financial inclusion. In contrast, the study by Khera et al. (2022) revealed that the weights assigned to the access to and use of DFSs were the same. This finding implies that these two subindices are equally prevalent. Access is strongly linked with the first axis and accounts for more than two-thirds (70.42%) of the total variance in the model. However, this does not fully capture DFI. All three dimensions indicate a shared underlying construct of DFI. Use also plays a substantial role, accounting for a notable proportion of the overall contribution (17.03%). A potential explanation could be the presence of inactive accounts within the user base of mobile financial services. According to GSMA surveys, a significant proportion of individuals possess a mobile financial account. However, approximately 25% of these accounts in developing nations were projected to remain inactive in 2021. This observation is noteworthy, considering the positive trajectory observed in the expansion of mobile account engagement from 2012 to 2021, with an increase from 12% to 26%.¹⁶ Furthermore, the significance of quality cannot be undermined as it accounts for 12.56% of the overall variance in the model. This demonstrates that regulating emerging technologies is crucial for influencing consumer trust and acceptance of DFSs.

Combining these three subindices results in the composite index of DFI, called the DFII. According to the latest Global Findex data, this index is currently considered the most up-to-date to the best of our knowledge.

Fig. 14 illustrates the progression of DFI across countries from 2014 to 2021. There is an observable upward trajectory from 2014 to 2017, which aligns with the findings of Khera et al. (2022). Furthermore, this tendency persists from 2017 to 2021 in all examined nations. The preference for rating countries by quantile is supported by Khera et al. (2022). Table 2 displays the DFI by quantile, categorizing nations into four groups based on their relative levels: *low*, *moderate*, *high*, and *very high*. Between 2014 and 2021, Kenya and Ghana emerged as the sole nations within the high echelons of DFI. In 2014, Mali was a member of the aforementioned group; however, it was displaced from its position by Côte d'Ivoire in 2017. Côte d'Ivoire ascended from its initial third place, surpassing Ghana and Kenya, to secure the second place in 2021, overtaking Ghana, which had held the leading position in this group in 2017. Kenya exhibited the greatest inclusion index in both 2014 and

¹⁶ <https://www.gsma.com/mobilefordevelopment/blog/mobile-money-activity-rates-exploring-barriers-to-regular-use/>, accessed on May 21, 2023, at 6.55 p.m.

2021. Kenya's prominent position is unsurprising given its recognition as the epicenter of Africa's financial technology revolution; this country is referred here to as the "rift valley of digital financial service." In contrast, Burkina Faso, Guinea, and Malawi exhibited limited levels of DFI during the entirety of the study period. Mali experienced a sharp change in its situation from 2017 onward and found itself aligned with this group of countries. The rapid decline of the subject caused it to shift to the opposite end of the spectrum from its original position in 2014. Regrettably, it has steadily failed to disassociate itself from its declining condition. In contrast, Cameroon, a member of this group in 2014, improved its condition in 2017. Cameroon facilitated the connection between nations exhibiting modest levels of financial inclusion, namely, Uganda and Zambia. The significance of this action should not be underestimated as Nigeria, which previously fell within this category in 2014, has now joined the ranks of countries with notable levels of financial inclusion, i.e., Senegal, Tanzania, and Zimbabwe. In 2021, Nigeria surpassed Zimbabwe in terms of performance (see Fig. 14).

Apparently, most countries with a low DFI level¹⁷—the first quantile—are characterized by low access, use, and quality levels, as shown in Figs. 15, 16 and 17, respectively. However, this is not the case for the groups of countries at the antipode—the fourth quantile¹⁸. As expected, Kenya is on an exceptional trajectory in terms of DFS use and quality. The descriptive analysis had already identified such a trend in relation to the use intensity of digital financial services. Thus, Kenya's leadership in DFI is possibly driven by both the high level of use and quality of DFSs.

Based on an analysis of score variation as depicted in Fig. 18, the growth rate in DFI exhibited a more rapid increase throughout the period from 2014 to 2021, compared to the preceding 2017–2014 period. Furthermore, substantial disparities exist in the rates of expansion of DFI across the nations under investigation during all the periods of comparison (2014–2017, 2014–2021, and 2017–2021).

This raises two questions: (i) *why has DFI grown exceptionally in all the countries studied in 2021? Specifically, could the onset of the 2020 health crisis be the predominant cause?* (ii) *To what extent do differences in the level of access, use, and quality of DFSs help explain the differences observed in the growth rates of DFI between the countries under review?*

4.5. Role of COVID-19 in accelerating digital financial inclusion

The impact of COVID-19 on the acceleration of digital financial inclusion is estimated based on the econometric strategy described below.

4.5.1. Estimation strategy

Our estimation strategy is as follows:

(a) We started estimating Equation (8) without considering the endogeneity problem. We compared fixed effects versus random effects models based on the Hausman test. Under the null hypothesis, the Hausman test suggests that the random effects model is consistent and efficient, meaning that the differences between the coefficients estimated by the fixed effects and random effects models are not systematic. This implies that the individual effects are uncorrelated with the regressors, and both models are equally efficient. Under the alternative hypothesis, the Hausman test posits that the fixed effects model is consistent and the random effects model is inconsistent, meaning that the individual effects are correlated with the regressors. This indicates systematic differences between the coefficients estimated by the two models; thus, the fixed effects model should be selected. The p-value (0.004) strongly supports the alternative hypothesis, indicating the suitability of the panel model with fixed effects.¹⁹

Table 3 reports the results of the fixed effects model. Using the stepwise procedure, we incorporated control variables from Columns (2)–(8). The results of our study indicate that COVID-19 exerts a significant and positive impact on DFI (Columns (1)–(5)). However, this impact becomes less pronounced and statistically insignificant when we introduce additional variables (Columns (6) and (7)) or when we control for all the specified macroeconomic variables (Column 8) in line with Equation (8). All other macroeconomic factors lack statistical significance, except for urban population share, financial account, and bank concentration. We cannot discuss these results at this stage due to the reverse causality between GDP and DFI.

(b) We adopted the IV approach to address the endogeneity issue.²⁰ We used the Hausman test to compare fixed effects combined with IVs²¹ and random effects with IVs. The null hypothesis of this test is that the random effects model with IV is consistent and efficient, meaning that the differences between the coefficients estimated by the fixed effects model with IV and the random effects model with IV are not systematic. Thus, the individual effects are uncorrelated with the regressors, and both models are equally efficient. Under the alternative hypothesis, the fixed effects model with IV is consistent and the random effects model with IV is inconsistent, meaning that the individual effects are correlated with the regressors. This indicates that there are systematic differences between the coefficients estimated by the two models; thus, the fixed effects model with IV should be preferred. The p-value of the test (0.7489) did not provide evidence to reject the null hypothesis. Using Equation (9), which yields the relationship between access to electricity and GDP, along with Equation (8), which yields the relationship between COVID-19 and DFI, we estimated the generalized two least stage square (G2SLS) with random effects, where GDP is treated as endogenous. To deal with heteroscedasticity, standard deviations were clustered at the country level. We report tests of instrument strength for all results employing IVs.

In Table 4, we report the first-stage relationship between the logarithm of GDP and that of access to electricity²²—our instrument. From Columns (2)–(8), we included control variables using the stepwise procedure. The order of inclusion of these variables did not affect the values of the estimated coefficients. This is the primary exercise for the robustness check. Data presented in the table reveal that the IV has a significant relationship with the logarithm of GDP. The F-statistic for the excluded instruments (Cragg–Donald or Kleibergen–Paap) is higher than Stock and Yogo's (2005) cutoffs for rejecting the null hypothesis of weak instruments at all percentages of the authorized bias of the IV estimator. Our instrument is therefore strong. However, we could not test the exogeneity condition because we had one endogenous regressor with a single instrument. In such a case, the coefficients are said to be precisely identified. In their famous book *Introduction to Econometrics*, Stock and Watson (2003, p. 443) argue that when the coefficients are exactly identified, it is not possible to test the hypothesis that the instruments are exogenous and then design a suitable statistical test.

Across all regressions, the effect of COVID-19 on DFI is positive and statistically significant. It can be argued that the COVID-19 pandemic has played an important role in expediting the progress of DFI. The conclusion drawn aligns with the findings of Fu and Mishra (2022). Their studies provided evidence that the observed rise in the download rate of mobile financial applications was associated with the emergence of the COVID-19 pandemic. Put differently, the health crisis coincided with a surge in DFI. Nevertheless, our findings are inconsistent with the research conducted by Sugandi (2021). According to the author, Fin-Tech activities in Indonesia were unaffected by the health crisis.

¹⁷ Represented by a red circle.

¹⁸ Represented by a green circle

¹⁹ We performed the Hausman test again to compare pooled ordinary least squares results with those of fixed effects. Based on the p-value (0.01) of this test, we still preferred the panel fixed effects model.

²⁰ We acknowledge again the anonymous reviewers for their helpful comments.

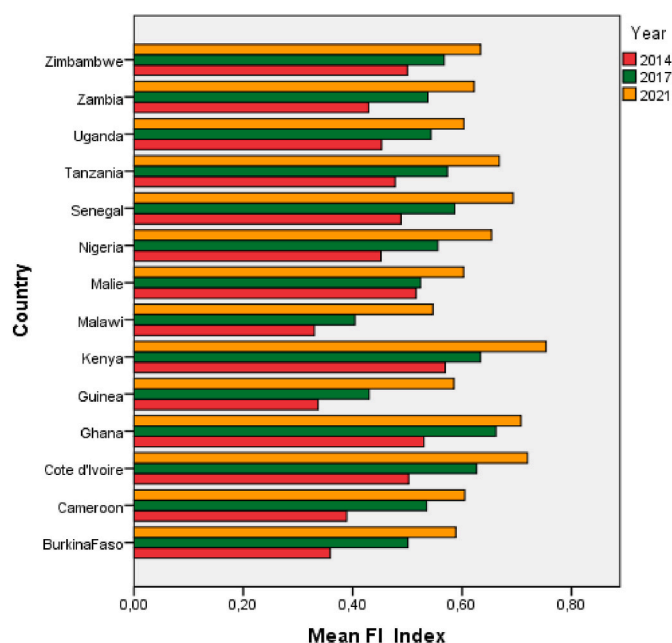
²¹ The results of the fixed effects model with IV are reported in the Appendix (see Table A5).

²² The data for this variable is sourced from the World Bank

Table 2

Digital financial inclusion scores by country and by quantile in 2014, 2017, and 2021.

2014				2017				2021			
Quantile	Country	Score	Rank	Quantile	Country	Score	Rank	Quantile	Country	Score	Rank
4	Kenya	0.57	1	4	Ghana	0.66	1	4	Kenya	0.75	1
	Ghana	0.53	2		Kenya	0.64	2		Côte d'Ivoire	0.72	2
	Mali	0.52	3		Côte d'Ivoire	0.63	3		Ghana	0.71	3
3	Côte d'Ivoire	0.50	4	3	Senegal	0.59	4	3	Senegal	0.69	4
	Zimbabwe	0.50	5		Tanzania	0.57	5		Tanzania	0.67	5
	Senegal	0.49	6		Zimbabwe	0.57	6		Nigeria	0.65	6
	Tanzania	0.48	7		Nigeria	0.56	7		Zimbabwe	0.63	7
2	Uganda	0.45	8	2	Uganda	0.54	8	2	Zambia	0.62	8
	Nigeria	0.45	9		Zambia	0.54	9		Cameroon	0.60	9
	Zambia	0.43	10		Cameroon	0.53	10		Uganda	0.60	10
1	Cameroon	0.39	12	1	Mali	0.53	12	1	Mali	0.60	12
	Burkina Faso	0.36	13		Burkina Faso	0.50	13		Burkina Faso	0.59	13
	Guyana	0.34	14		Guyana	0.43	14		Guyana	0.58	14
	Malawi	0.33	15		Malawi	0.40	15		Malawi	0.55	15

**Fig. 14.** Evolution of the financial inclusion index from 2014 to 2021 by country.

Therefore, the extent to which it enhances DFI is uncertain. Nevertheless, the research conducted by the author in question is limited in scope, since it primarily concentrates on a singular country. Consequently, it is imperative to use caution when attempting to generalize the author's conclusion to other nations.

In addition to the impact of COVID-19 on DFI, other macroeconomic factors have also explained this primary variable of interest. Of all the variables considered, both GDP and the quality of governance have significantly influenced DFI. When all additional factors are incorporated into the regression analysis (Column 7 of Table 4), a 1% rise in GDP would result in a 0.35% increase in DFI. The literature on financial inclusion clearly supports the direction of this relationship. Similarly, institutional characteristics such as the rule of law displayed the same magnitude as GDP on DFI. Increasing the rule of law index by one unit would result in a 0.36% increase in DFI. The positive and significant impact of the rule of law aligns with the findings of Khera et al. (2021). They have shown that higher institutional quality is associated with more mobile money agents. In contrast, demographic factors, specifically the urban population proportion, have negatively and statistically significantly impacted DFI. Thus, as the proportion of the urban

population increases, the level of DFI drops. Khera et al. (2021) likewise observed this inverse association; however, the influence of the second variable on the first was insignificant. We contend that the direction of this relation is influenced by the demographic composition of the countries, where the proportion of older individuals residing in urban areas exceeds that of younger individuals in urban areas. It would be appropriate to examine the influence of demographic characteristics on DFI by analyzing the proportion of the urban population separately for both younger and older age groups. Macroeconomic data did not, however, allow us to undertake this kind of exercise.

Other macroeconomic variables did not impact DFI. Inefficiency in the banking sector was positive but insignificant in terms of bank overhead costs. This result means that the high overhead costs of banks are associated with a higher level of DFI, implying that inefficiencies in bank operations create gaps in providing financial services to a wider population. Still, this gap does not seem to be completely filled by new digital players. This is the main rationale explaining the lack of statistical significance in the bank overhead costs—DFI nexus. In return, as measured by bank concentration, inefficiency in the banking sector was found to be negative; however, it was insignificant. As Khera et al. (2021) observed, this implies that the presence of big dominant banks could hinder the development of digital financial providers, and per our findings, their power was not found to be sufficient to inhibit both the emergence and growth of DFSs. The banking level (financial account and debit card) was also found to be insignificant. This implies that DFI increases irrespective of the banking level.

To appreciate the strength of our results, we conducted a robustness check. The results are presented in Table A6 (see Appendix). For each country, we computed the average values of several variables, such as GDP, bank concentration, and bank overhead, during three distinct periods: 2008–2013, 2014–2016, and 2017–2020. Those values have been used in the corresponding periods included in our sample. Our instrument remained strong even when we included additional variables namely foreign direct investment or private credit.²³ Comparing the final results of Column 7 of Table 4 with the estimated results in Column 7 of Table A6—after averaging data for the specified variables and including additional variables—the significance, and direction of the coefficients²⁴ of COVID-19 and control variables did not change, while the magnitude of the coefficients of the control variables changed slightly. Given these findings, it appears that our results are robust.

²³ We did not present the results using private credit due to space limitations.

²⁴ The direction of the coefficient of logarithm of bank overhead cost was an exception.

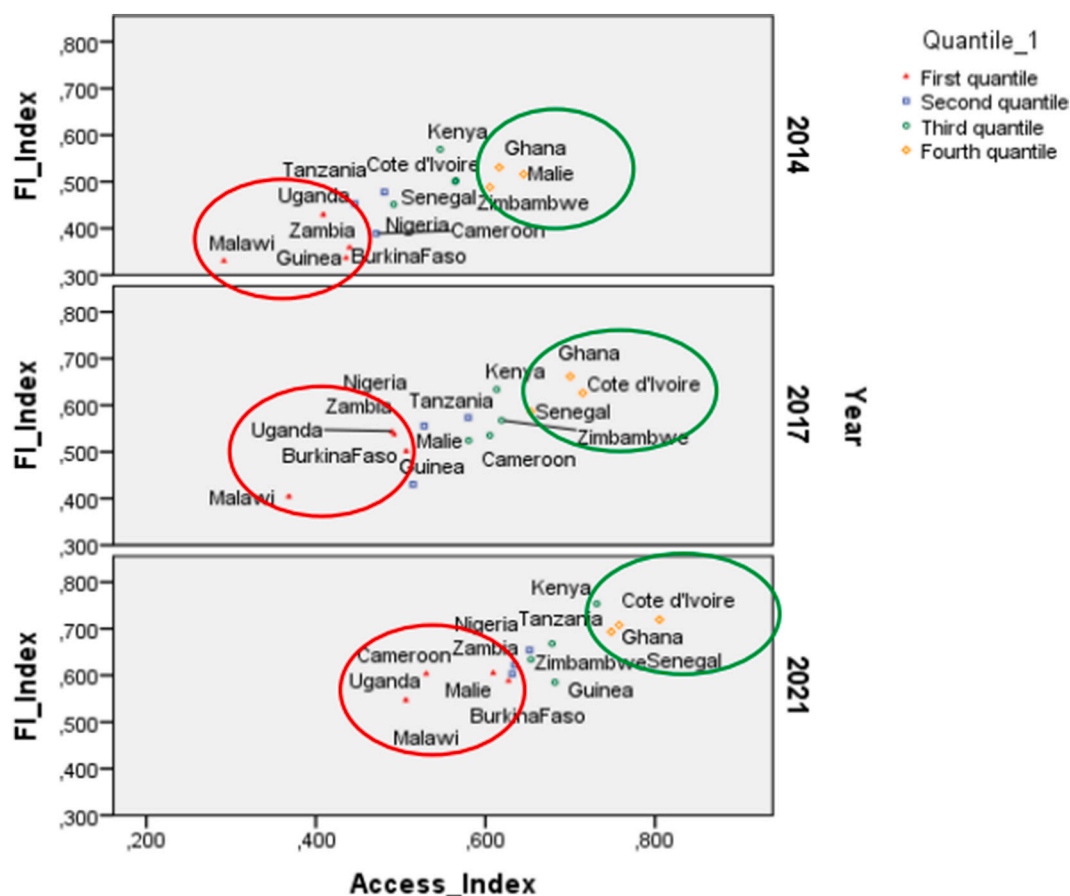


Fig. 15. Intersection of digital financial inclusion and access by country and quantile between 2014 and 2021.

4.6. Decomposition of digital financial inclusion growth rates

Klapper (2015), cited by Burjorjee & Scola (2015, p. 1), cautions against the enduring notable disparities in the access, quality and use of DFSs accessible in the market, notwithstanding the global progress in achieving comprehensive financial inclusion. To assess the impact of these variations on the level of financial inclusion in a region, we undertook a decomposition analysis. As this analysis pertains to inequality, we used the Shapley decomposition analysis. The Shapley value decomposition analysis, developed by esteemed American mathematician and economist Lloyd Shapley in 1953, has been successfully applied in diverse domains such as economics, game theory, machine learning, and the interpretability of prediction models.

The Shapley decomposition methodology facilitates the evaluation of the relative significance of individual variables or characteristics within an intricate system, by quantifying their respective contributions to the total value or performance. Therefore, it provides a comprehensive understanding of individual components' contributions to the outcome. This methodology is especially advantageous in cases in which a system exhibits intricate interdependencies between its components, making it challenging to ascribe specific contributions to components. DFI encompasses various interconnected elements; therefore, this approach is suitable in this field.

In the area of inequality, particularly income inequality, the decomposition technique affords researchers the ability to discern the intergroup effect arising from income disparities between distinct subgroups (such as men and women) from the intragroup effect stemming from inequality within a given group (Shorrocks, 1999, p. 99). The research conducted by Aslan et al. (2017) aligns with this theoretical paradigm. The Gini inequality index of financial inclusion was decomposed by the latter into intra- and intergroup inequality. Based on their

findings, disparities in the availability of financial services among genders (intergroup inequality) have a significant role in elucidating the disparities observed in financial inclusion. This article examines inequality by analyzing the varying growth rates in DFI among the countries included in the sample. The Shapley decomposition method, encompassing a broader range of factors compared to the decomposition technique employed by Aslan et al., allows us to comprehend the impact of variations in access, usage, and quality of financial services across country on the growth rate disparities of DFI.

According to Shorrocks (2013, p. 101), the Shapley solution considers “the marginal effect on the inequality of eliminating each of the contributory factors in sequence, and then assigns to each factor the average of its marginal contributions in all possible elimination sequences.” In other words, for Shapley decomposition, the rule for estimating the inequality index for a subset of components is suppressing the inequality generated by the complement subset of components (Araar & Duclos, 2021, p.58). The decomposition of total inequality indices into a sum of the contributions generated by separate income components consists of estimating (Araar & Duclos, 2021, p.58) (i) the share in total income of each income source k ; (ii) the absolute contribution of each source k to the Gini index; and (iii) the relative contribution of each source k to the Gini index. When applied to regression-based decomposition of inequality, the Shapley approach estimates the expected marginal contribution of income sources to total inequality (Araar & Duclos, 2021, p.60). We replaced income with the DFI and its source with the DFI components or dimensions. We then computed the relative contribution of each element of DFI, specifically the difference in access, usage, and quality, to the Gini index of DFI

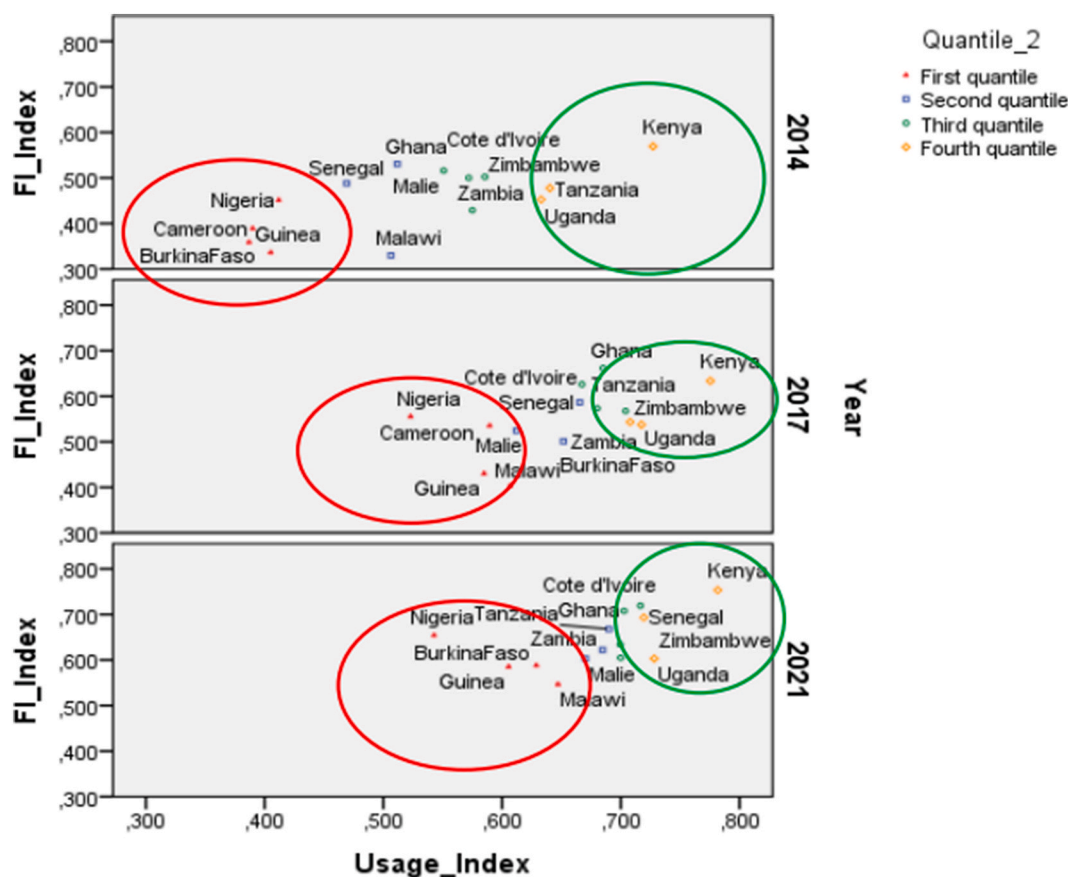


Fig. 16. Intersection of digital financial inclusion and usage by country and quantile between 2014 and 2021.

growth using regression-based decomposition of inequality²⁵.

Our study's findings, presented in Table 5 indicate that approximately one-third of the variations in growth rates of DFI may be attributed to disparities in the use of financial services among the examined countries. This relationship holds true regardless of whether the inequality measure employed is the Gini index or the variation coefficient. Furthermore, the variations in the extent of access to DFSs among the examined countries contribute to approximately 13% of the disparities in growth rates pertaining to DFI. The variations observed in the quality of financial services yield a minimal contribution, amounting to a mere 2%. Nevertheless, there is a substantial proportion of unexplained or residual share in the decomposition of both the Gini index (50.27%) and coefficient of variation (52.02%). Based on intuition, we infer that structural disparities in these countries play a significant role in elucidating the variations in growth rates pertaining to DFI. This aligns with the Institute of Digital Finance's (2019, p.13) argument that financial inclusion status can vary annually within a region and differ between regions in the same year due to disparities in natural endowment, economic development and structure, policies, and institutions.

We now address inequality in the use and accessibility of financial services. The primary inquiry is as follows: What are the potential factors contributing to the observed inequality?

4.6.1. Determinants of inequality in both accessibility and use of digital financial services²⁶

The literature on the gap in financial inclusion highlights four dimensions that impede the progress of financial inclusion, contributing to

disparity in financial access and use of innovative financial services. Our focus here is on the dimensions for which we have available data. The determinants, many identical to those previously mentioned, include economic development, financial sector inefficiencies, institutional factors and macroeconomic constraints.

- Economic development: Sarma and Pais (2011) showed that a high level of financial inclusion is associated with a high level of economic development. GDP is the most commonly used indicator to capture a country's economic development level. It appears that differences in GDP between countries could result in uneven DFI for those countries.
- Financial sector inefficiencies: It is widely argued that inefficiencies in the financial sector, such as bank concentration and high overhead cost, could hinder financial inclusion. Bank concentration refers to the dominant position of banks, which might impede financial system reforms intended to allow nonbank actors to participate in the financial system. Overhead costs refer to the significant administrative expenses associated with opening and maintaining a financial account at a financial institution.
- Institutional factors: Many papers have demonstrated that the "financial system will develop more fully in countries with the observance of the law, political stability, fair and efficient enforcement of the rule of law and respect for creditors and debtors' rights" (Rojas-Suárez and Amado (2014)). Moreover, Rojas-Suárez and Amado (2014) predicted that countries with worse institutional deficiencies (poorer governance quality) may face more obstacles in their efforts to enhance financial inclusion. Following Rojas-Suárez and Amado (2014), Rojas-Suárez (2016),

²⁵ See Aarar and Duclos (2021) for more details

²⁶ We acknowledge the anonymous reviewers again for their valuable suggestions

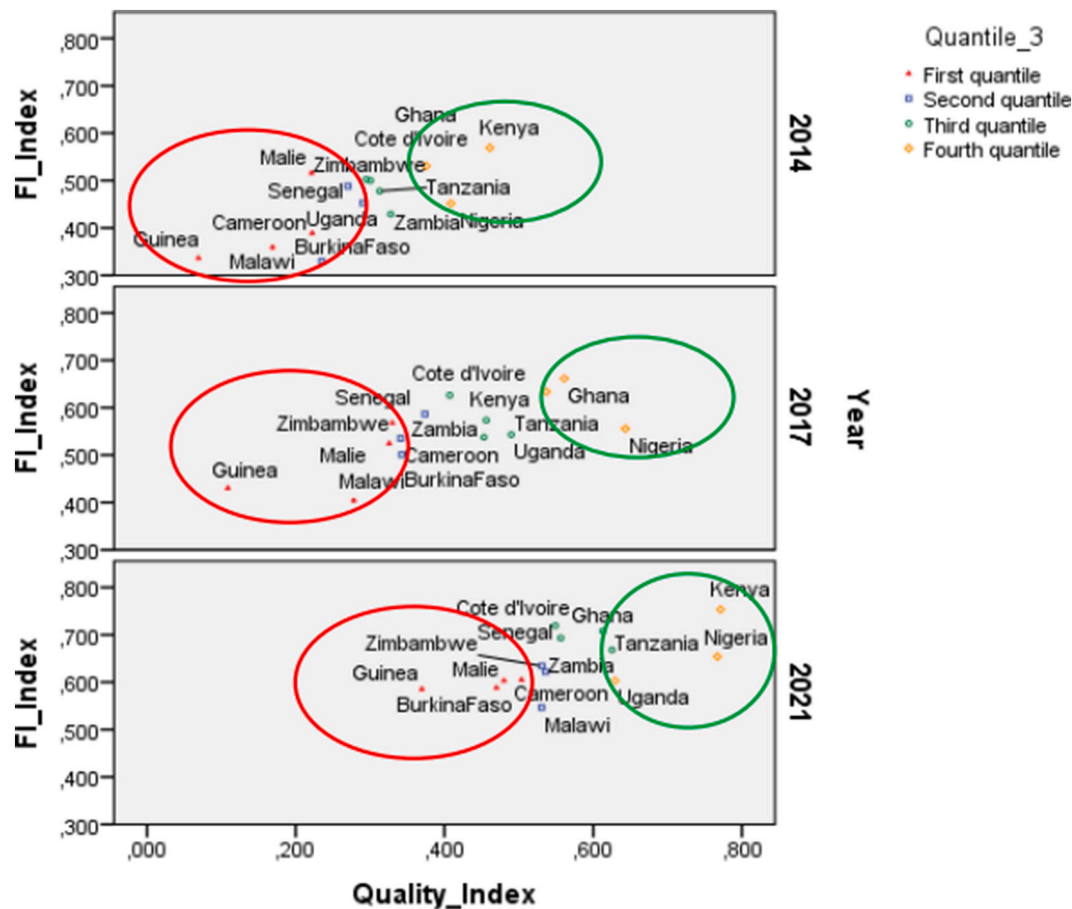


Fig. 17. Intersection of digital financial inclusion and quality by country and quantile between 2014 and 2021.

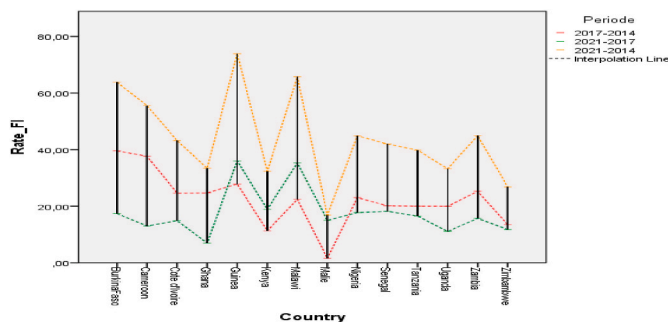


Fig. 18. Comparison of digital financial inclusion growth rates by country.

and Khera et al. (2021), we used the rule of law as a proxy for governance quality.

- (d) Macroeconomic constraints: During periods of high and volatile inflation, depositors experience significant losses in real terms, reflected in negative and volatile real interest rates (Rojas-Suárez, 2016). These memories persist for an extended period and serve as a significant disincentive to save through financial institutions. Thus, inflation volatility could discourage using DFSs such as mobile savings or credit.

However, we did not incorporate such information into our use index owing to data unavailability. Therefore, we preferred to use financial depth proxied by private credit (*Privcred*) as an additional macroeconomic variable. This was implemented because when countries achieve a high degree of financial depth, the disparity in the access to and use of

DFSs will likely be reduced. This is because individuals in these countries have already established trust in banking services and have consequently acquired a habit of using them. Consequently, the wider population can easily adopt and use DFSs. Kenya and Senegal exemplify countries in SSA that perform well in terms of financial depth. The ratio of private credit to GDP is 32.83% for Kenya and 28.23% for Senegal on average. Additionally, these countries exhibit a high level of DFI. Furthermore, research on finance and inequality has shown that income inequality decrease as economies develop their financial systems (see Clarke et al., 2003), supporting the U-shaped theory introduced by Greenwood and Jovanovic (1990).

Most of the research on inequality or gap in financial inclusion is cross-sectional. Moreover, this gap is computed using financial services provided by traditional financial players. In addition to applying the inequality measure to both access to and use of DFSs, to our knowledge, this is the first study that uses panel data to address the issue of inequality in financial inclusion. Furthermore, we expanded the existing set of variables by including the legal origin (*Legorig*), based on the research conducted by La Porta et al. (1998). They noted that countries usually acquired their legal systems through force, such as conquest or colonization. Consequently, the legislation governing digital banking and financial institutions is influenced by the legal codes inherited from countries with civil law traditions, such as the French civil law system and the common law legacy of England. Consistent with the findings of La Porta et al. (1998), common law countries provide the highest legal protections for shareholders, while countries with French civil law offer the lowest legal protections. This suggests that countries that inherited common law are likely to have less inequality in terms of financial access and usage of DFSs compared to those inherited by French civil law. The explanation is that countries with the highest legal protection are likely

Table 3

Results of the fixed effects model.

	1	2	3	4	5	6	7	8
Dependent variable: Log (DFII)								
Covid_19	0.11*** (0.01) ¹	0.09*** (0.01)	0.10*** (0.02)	0.09*** (0.02)	0.09*** (0.02)	0.04 (0.02)	0.04 (0.02)	0.03 (0.02)
Log (GDP)		0.91*** (0.25)	0.75*** (0.23)	0.72** (0.30)	0.64* (0.29)	0.21 (0.22)	0.06 (0.23)	0.09 (0.23)
Log (Bank concentration)			−0.16 (0.10)	−0.16 (0.10)	−0.12 (0.12)	−0.15 (0.10)	−0.13 (0.10)	−0.14* (0.07)
Log (Bank overhead cost to assets)				−0.04 (0.18)	−0.04 (0.17)	−0.04 (0.14)	0.01 (0.13)	0.01 (0.12)
Log (Rule of Law)					0.27 (0.20)	0.23 (0.14)	0.15 (0.15)	0.08 (0.16)
Log (Urban population)						0.91*** (0.23)	0.87*** (0.21)	0.91*** (0.23)
Log (Financial account)							0.14* (0.23)	0.25*** (0.08)
Log (Debit Card)								−0.12 (0.09)
Constant	−0.31*** (0.03)	−3.01*** (0.77)	−2.33** (0.79)	−2.21* (1.12)	−1.94* (1.94)	−3.83*** (1.04)	−3.50*** (1.04)	−3.79** (0.93)
Observations	42	42	42	42	42	42	42	42
R-squared (overall)	0.37	0.38	0.43	0.45	0.50	0.05	0.05	0.05

⁽¹⁾: Values in parentheses refer to the clustered standard errors estimated at the country level.

***, **, and *: denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4

Results of the G2LS random effects model.

	1	2	3	4	5	6	7
Second-stage regression							
Dependent variable: Log Financial inclusion							
Log (Real GDP)	0.27*** (0.05) ¹	0.18** (0.07)	0.17** (0.07)	0.22*** (0.07)	0.39*** (0.13)	0.40*** (0.10)	0.35*** (0.08)
Weak Identification Test	C-D ^c K-P ^d	76.97+++	40.41+++	37.89+++	32.92+++	27.51+++	29.90+++
R-Squared (Overall)	0.58	0.66	0.68	0.68	0.74	0.74	0.74
First-stage regression							
Dependent variable: Log Real GDP							
Log (Electricity)	0.70*** (0.05)	0.54*** (0.06)	0.53*** (0.06)	0.48*** (0.07)	0.37*** (0.07)	0.36*** (0.07)	0.42*** (0.06)
Observation	42	42	42	42	42	42	42
Variables included in first- and second-stage regressions							
Covid_19	0.10*** (0.01)	0.11*** (0.01)	0.11*** (0.01)	0.11*** (0.01)	0.12*** (0.01)	0.12*** (0.02)	0.11*** (0.02)
Log (Bank concentration)		−0.19* (0.12)	−0.19 (0.12)	−0.12 (0.14)	−0.03 (0.15)	0.03 (0.14)	−0.01 (0.11)
Log (Bank overhead)			−0.06 (0.04)	−0.03 (0.05)	0.02 (0.07)	0.04 (0.05)	0.04 (0.04)
Log (Rule of Law)				0.26 (0.17)	0.43** (0.19)	0.46* (0.18)	0.36** (0.15)
Log (Urban population)					−0.11*** (0.04)	−0.12*** (0.04)	−0.10*** (0.03)
Log (Financial Account)						0.02 (0.06)	0.12 (0.13)
Log (Debit Card)							−0.08 (0.10)
Constant	−1.13*** (0.15)	−0.55 (0.42)	−0.46 (0.40)	−0.66 (0.41)	−0.91* (0.51)	−1.05** (0.47)	−0.97** (0.38)

⁽¹⁾: Values in parentheses refer to the clustered standard errors estimated at the country level; (a): refers to the Cragg–Donald Wald F statistic and (b) to the Kleibergen–Paap rk Wald F statistic. Both statistics are compared to the critical values of Stock and Yogo. For K1 = 1 and L1 = 1 (one endogenous regressor), the Stock and Yogo critical values are 16.38, 8.96, 6.66, and 5.53 corresponding to 10%, 15%, 20%, and 25% maximal IV size, respectively, the bias percentages that are acceptable for IV estimator. +++: Statistically significant at all critical values of Stock and Yogo. ***, **, and *: denote significance at the 1%, 5%, and 10% levels, respectively.

to attract more investment in the banking sector than those with the lowest legal protection. Put simply, the legal origin is a factor that contributes to inequality in financial inclusion, namely in terms of the disparity in access to and use of DFSs. Ultimately, we hypothesized that COVID-19 might narrow the discrepancy between countries with advanced DFI and those with limited or moderate DFI. According to the

Global Findex database, more than one-third of people began using mobile devices to make commercial bill payments for the first time during the COVID-19 outbreak.

Based on the above, our econometric model can be written as follows:

Table 5
Decomposition of digital financial inclusion growth rates.

Relative contribution (%)		
	Gini index	Coefficient of variation
Access	13.52	12.88
Use	33.85	32.97
Quality	2.36	2.11
Residual share	50.27	52.02

$$\begin{aligned} \text{Log}(\text{Access gini index})_{it} = & c_1 + c_2(\text{Covid})_{it} + c_3 \text{Log}(\text{GDP})_{it} \\ & + c_4 \text{Log}(\text{BankConc})_{it} \\ & + c_5 \text{Log}(\text{BankOv})_{it} + c_6 \text{Log}(\text{RL})_{it} + c_7 \text{Log}(\text{Privcred})_{it} + c_8 \text{Log}(\text{Legorig})_{it} + u_{it}. \end{aligned} \quad (10)$$

$$\begin{aligned} \text{Log}(\text{Usage gini index})_{it} = & d_1 + d_2(\text{Covid})_{it} + d_3 \text{Log}(\text{GDP})_{it} + d_4 \text{Log}(\text{BankConc})_{it} \\ & + d_5 \text{Log}(\text{BankOv})_{it} + d_6 \text{Log}(\text{RL})_{it} + d_7 \text{Log}(\text{Privcred})_{it} + d_8 \text{Log}(\text{Legorig})_{it} + d_9 \text{Log}(\text{inter})_{it} + d_{10} \text{Log}(\text{Mobsus})_{it} + u_{it}. \end{aligned} \quad (11)$$

With *Legorig* a dummy variable that equals 1 if a country has common law rules and 0 otherwise. Exceptionally, we included in Equation (11) internet (*inter*) and mobile subscription (*mobsus*), which are the variables that could affect using DFSs. On the left side of Equations (10) and (11), we computed the Gini index for access to/usage of DFSs at the year level. The values of this index were taken in logarithms afterward.

To avoid reverse causality or bias from omitted variables, we replaced the variables on the right side of Equations (10) and (11) by their first lag following [Alfar et al. \(2023\)](#), except for COVID-19 and legal origin, which are the dummy variables.

The results of the random effects model for both inequalities in access to and use of DFSs are presented in [Tables 6 and 7](#), respectively. The Breush–Pagan Lagrange multiplier²⁷ and Hausman tests validated the statistical significance of the random effects. When all variables are included in the regression analysis, the results in Column 7 of [Table 6](#) indicate that the primary factor that positively and significantly accounts for the inequality in access to DFSs is the legal origin. As anticipated, the Gini index for access to DFSs is marginally higher in nations with a legal system based on French civil law (0.12) than those with a legal system based on English common law (0.09). Other macroeconomic factors, such as growth in domestic product per capita, financial inefficiency in terms of bank concentration and the rule of law, drive inequality in access to DFSs but their effect were not found to be statistically significant.

Conversely, financial inefficiency in terms of bank overhead costs and financial depth have reduced inequality in access to DFSs. This applies particularly to countries that transition from one quantile to another or see a shift in their position within the same quantile. As noted earlier, inefficiencies in bank operations create gaps in the provision of financial services to wider populations, which new digital players significantly reduce. Financial depth through private credit reduces inequality in access to DFSs, thanks to the population's trust in and culture related to using banking services. COVID-19 was also a factor contributing to reducing inequality in access to DFSs. Evidence of data from Global Findex has previously confirmed this fact.

Regarding the inequality in using DFSs, our reported findings in the

last column of [Table 7](#) reveal that legal origin and internet access are the main drivers of this form of inequality. Legal origin explains this primary variable of interest in terms of both using offline and online financial services. In return, access to the internet describes it in terms of using online financial services. The mobile subscription was found to be positive, but its effect was not statistically significant. We highlighted earlier that in developing countries, thanks to social ties, people can use DFSs through the phones of their relatives. This could support the statistically insignificant effect of mobile subscriptions on inequality in using DFSs. Furthermore, the widespread availability of mobile phones at a lower cost makes it much more compelling to endorse this outcome. Other macroeconomic variables, such as growth product per capita, financial inefficiency in terms of bank concentration and financial depth, and COVID-19, were the factors that significantly reduced inequality in using DFSs. This statement is especially true for countries

that transitioned from one quantile to another or for those that experienced a shift in position within the same quantile.

5. Conclusion

The composite DFII emphasizes the degree of DFI within the countries in SSA. According to this index, several countries exhibit a notable degree of DFI, including Kenya, Ghana, and Côte d'Ivoire. In contrast, certain countries such as Mali, Burkina Faso, Guinea, and Malawi exhibit a lower degree of DFI. The DFI index employed in this paper has effectively illuminated the discrepancies that exist between the studied nations. Nevertheless, a prevailing pattern was observed in all nations, indicating a rise in DFI in SSA from 2014 to 2021. DFI grows substantially from 2021 to 2014; this trajectory is more remarkable compared with the growth observed between 2017 and 2014. Using the IV approach, we found that COVID-19 was a factor contributing to the observed outcome. Moreover, other macroeconomic variables such as growth product per capita and governance quality were the main drivers of DFI. Notable disparities in the expansion rates of DFI were also observed. Approximately 30% of these disparities could be attributed to variations in the use of DFSs among the examined nations. However, a significant portion of these disparities, specifically 50%, can be traced to the structural variations in these nations. To enable countries with low DFI to catch up with countries with high DFI, it is necessary to implement policies that prioritize the use of financial services. Financial and digital education could be the two mechanisms to strengthen DFI or even traditional financial inclusion. In addition, concrete actions need to be undertaken to strengthen access to DFSs. Although most African countries have achieved a reasonable level of mobile network coverage, differences in mobile network access exist between urban and rural areas. Encouraging the large-scale deployment of mobile telephone operators in disadvantaged areas (particularly rural areas) would improve access to DFSs.

Furthermore, we described the factors that explain the inequality in access to and use of DFSs. We found that the legal origin is a driver of inequality in the accessibility and use of DFSs. Moreover, access to the internet has contributed to inequality in the use of DFSs. In terms of economic implications, countries with the lowest DFI need to revise their legal systems and invest in internet infrastructure. In addition to facilitating DFI, high level of internet development can boost the economy effectively ([Lee et al., 2023](#), p. 423).

This study has certain limitations. The DFII fails to adequately

²⁷ The null hypothesis of this test is that variances across entities are equal to zero. Thus, there is no significant difference across units (i.e., no panel effect).

Table 6

Determinants of inequality in access to digital financial services.

	1	2	3	4	5	6	7
Dependent variable: Log (Access Gini index)							
Covid_19	−0.35*** (0.00) ¹	−0.34*** (0.00)	−0.33*** (0.01)	−0.32*** (0.01)	−0.32*** (0.01)	−0.31*** (0.01)	−0.29*** (0.02)
Log (GDP (−1))		0.03 (0.08)	0.10 (0.10)	0.03 (0.09)	0.04 (0.10)	0.01 (0.13)	0.02 (0.12)
Log (Bank concentration (−1))			0.15 (0.18)	0.10 (0.13)	0.10 (0.13)	0.02 (0.16)	0.09 (0.16)
Log (Bank overhead cost (−1))				−0.25*** (0.07)	−0.24*** (0.08)	−0.41*** (0.07)	−0.48*** (0.06)
Log (Rule of Law (−1))					0.02 (0.22)	0.06 (0.18)	0.11 (0.17)
Log (Private credit (−1))						−0.23*** (0.06)	−0.25*** (0.04)
Legal origin (Common law)							0.06** (0.02)
Constant	−2.35*** (0.02)	−2.47*** (0.25)	−2.93*** (0.56)	−2.45*** (0.50)	−2.47*** (0.50)	−1.85*** (0.61)	−1.95*** (0.59)
Observations	41	41	41	41	41	41	41
R-squared	0.77	0.77	0.78	0.82	0.82	0.86	0.88

⁽¹⁾: Values in parentheses refer to the clustered standard errors estimated at the country level.

***, **, and *: denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7

Determinants of inequality in use of digital financial services.

	1	2	3	4	5	6	7	8
Dependent variable: Log (Use Gini index)								
Covid_19	−0.43*** (0.00) ¹	−0.42*** (0.01)	−0.39*** (0.04)	−0.34*** (0.04)	−0.34*** (0.05)	−0.27*** (0.06)	−0.31*** (0.05)	−0.32*** (0.05)
Log (GDP (−1))		0.12 (0.27)	0.34 (0.33)	0.10 (0.31)	0.12 (0.34)	0.06 (0.03)	−0.83*** (0.19)	−0.87*** (0.20)
Log (Bank concentration (−1))			0.48 (0.58)	0.30 (0.43)	0.32 (0.42)	0.30 (0.51)	−0.02 (0.33)	−0.04 (0.32)
Log (Bank overhead cost (−1))				−0.80*** (0.25)	−0.79*** (0.27)	−1.57*** (0.20)	−0.99*** (0.15)	−0.99*** (0.13)
Log (Rule of law (−1))					0.08 (0.70)	0.35 (0.56)	−0.43 (0.41)	−0.48 (0.39)
Log (Private credit (−1))						−0.81*** (0.23)	−0.59*** (0.12)	−0.65*** (0.10)
Legal Origin						0.19** (0.07)	0.18*** (0.05)	0.19*** (0.06)
Log (Internet (−1))							0.78*** (0.07)	0.72*** (0.09)
Log (Mobile subscription (−1))								0.13 (0.11)
Constant	−2.57*** (0.06)	−2.96*** (0.82)	−4.47** (0.11)	−2.89*** (1.62)	−2.96* (1.64)	−1.27 (1.96)	0.14 (1.03)	−0.18 (1.06)
Observations	41	41	41	41	41	41	41	41
R-squared	0.32	0.32	0.34	0.47	0.47	0.63	0.86	0.87

⁽¹⁾: Values in parentheses refer to the clustered standard errors estimated at the country level.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

consider the digital divide, encompassing disparities in both access to and use of DFSs. The Global Findex database lacks the capacity to provide comprehensive data that are necessary for this purpose. Furthermore, the DFII framework is constructed using a limited set of nations from the SSA region, primarily owing to limitations in data availability. Moreover, data pertaining to the quality of digital infrastructure, as presented in the Network Readiness Index reports, are accessible only for a subset of SSA countries. Consequently, econometric estimations are conducted using a limited sample size. In this particular scenario, the application of structural break tests is not recommended to avoid biased results, as evidenced by the findings of [Bai and Perron \(2006\)](#). Their study demonstrates that various factors, including sample size, can substantially influence the power of structural break tests. Furthermore, similar to other indices, the DFII fails to encompass additional dimensions indicative of DFI. These dimensions include the costs associated with DFSs, obstacles hindering digital financial access, and the

impact of using DFSs. Regrettably, the availability of such information is limited in numerous developing nations.

Moreover, despite the reverse causality between our index and GDP, as explained in our research, our results remain robust even when we aggregate data for multiple variables over distinct periods and incorporate other macroeconomic variables. This is primarily because we employed the IV approach to address this problem.

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Ethical statement

The corresponding author and the co-author jointly certify that their institution has approved the protocol for any investigation involving human subjects and that all data used in this study was collected in conformity with ethical and humane principles of research.

CRedit authorship contribution statement

Christian Kamenga Mapurita: Conceptualization, Project

administration, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Célestin Mayoukou:** Writing – review & editing, Supervision, Validation.

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Appendix

Table A1
Correlation matrix per dimension

		Access				Usage				Quality	
		LogK1	LogK2	LogK3	LogK4	LogL1	LogL2	LogL3	LogL4	LogM1	LogM2
Access	LogK1	1									
	LogK2	0.48***	1								
	LogK3	0.63***	0.36***	1							
	LogK4	0.30**	0.26**	0.18	1						
Usage	LogL1					1					
	LogL2					0.76***	1				
	LogL3					0.87***	0.78***	1			
	LogL4					0.75***	0.49***	0.70***	1		
	LogL5					0.55***	0.63***	0.69***	0.54***		
Quality	LogM1									1	
	LogM2									0.50***	1
KMO		0.67				0.78				0.50	
Bartlett's Statistics		34.54***				159.26***				10.82***	

Table A2
Variables and their respective contributions to the factorial axis

Attributes	Access				Usage					Quality	
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC5	PC1	PC2
LogK1	0.335	0.235	0.147	0.901							
LogK2	0.155	0.959	0.121	0.202							
LogK3	0.938	0.161	0.067	0.298							
LogK4	0.062	0.113	0.985	0.118							
LogL1					0.496	0.444	0.194	0.336	0.658		
LogL3					0.377	0.421	0.355	0.673	0.320		
LogL4					0.912	0.176	0.236	0.196	0.206		
LogL5					0.232	0.271	0.908	0.184	0.124		
LogM1										0.253	0.967
LogM2										0.967	0.253
Eigenvalues	2.150	0.867	0.637	0.346	3.717	0.559	0.453	0.173	0.098	1.490	0.510

Table A3
Correlation test and data factorization

	Access	Usage	Quality
Access	1		
Usage	0.49***	1	
Quality	0.57***	0.61***	1
KMO		0.70	
Bartlett's sphericity test		35.27***	

Table A4
Subindexes and their respective contribution to the factorial axis

	PC1	PC2	PC3
Access	0.940	0.221	0.259
Usage	0.226	0.930	0.289
Quality	0.279	0.303	0.911
Eigenvalues	2.113	0.511	0.376

Table A5
Result of the fixed effects model with IV

	1	2	3	4	5	6	7
Second-stage regression							
Dependent variable: Log Financial inclusion							
Log (real GDP)	2.91 (2.6) ¹	2.74 (1.98)	2.28*** (0.87)	2.28** (0.95)	−0.12 (1.70)	−1.85 (5.65)	−2.87 (5.62)
Weak Identification Test	C-D ^a 0.66	1.15	2.68	2.18	0.29	0.11	0.19
R-square (overall)	K-P ^b 1.35 0.27	1.67 0.28	4.99 0.28	4.90 0.28	0.27 0.02	0.11 0.03	0.21 0.03
First-stage regression							
Dependent variable: Log Real GDP							
Log (Electricity)	0.06 (0.05)	0.08 (0.06)	0.12** (0.05)	0.11** (0.05)	0.05 (0.09)	0.03 (0.09)	0.04 (0.09)
Observation	42	42	42	42	42	42	42
Variables included in first- and second-stage regressions							
Covid_19	0.03 (0.08)	0.03 (0.07)	0.07* (0.03)	0.07* (0.04)	0.04 (0.03)	0.03 (0.06)	0.02 (0.07)
Log (Bank concentration)		0.08 (0.31)	0.01 (0.18)	0.01 (0.18)	−0.18 (0.17)	−0.24 (0.33)	−0.31 (0.35)
Log (Bank overhead)			0.14 (0.25)	0.14 (0.26)	−0.07 (0.25)	−0.13 (0.53)	−0.21 (0.55)
Log (Rule of Law)				−0.01 (0.32)	0.28 (0.20)	0.33 (0.60)	0.39 (0.68)
Log (Urban population)					1.01* (0.59)	1.36 (1.57)	1.65 (1.60)
Log (Financial Account)						0.25 (0.31)	0.37 (0.30)
Log (Debit Card)							−0.06 (0.22)
Constant	−9.21 (7.96)	−8.86 (6.52)	−7.40** (3.01)	−7.42** (3.26)	−3.01 (3.79)	0.79 (12.52)	2.98 (14.40)

(¹): Values in parentheses refer to the clustered standard errors estimated at the country level; (a): refers to the Cragg–Donald Wald F statistic and (b) to the Kleibergen–Paap rk Wald F statistic. Both statistics are compared to the critical values of Stock and Yogo. For K1 = 1 and L1 = 1 (one endogenous regressor), the Stock and Yogo critical values are 16.38, 8.96, 6.66, and 5.53 corresponding to 10%, 15%, 20%, and 25% maximal IV size, respectively, the bias percentages that are acceptable for IV estimator. +++: Statistically significant at all critical values of Stock and Yogo. ***, **, and *: denote significance at the 1%, 5%, and 10% levels, respectively.

Table A6
Robustness check

	1	2	3	4	5	6	7	8
Second-stage regression								
Dependent variable: Log Financial inclusion								
Log (Averaged real GDP)	0.32*** (0.07) ¹	0.17** (0.06)	0.16** (0.06)	0.20*** (0.05)	0.34*** (0.08)	0.32*** (0.08)	0.30*** (0.09)	0.32*** (0.10)
Weak Identification Test	C-D ^c 50.66+++	33.89+++	37.60+++	32.84+++	19.29+++	30.87+++	43.36+++	45.48+++
R-Squared (Overall)	K-P ^d 68.78+++	31.49+++	34.81+++	35.68+++	36.70+++	52.09+++	54.37+++	45.82+++
First-stage regression								
Dependent variable: Log Real GDP								
Log (Electricity)	0.58*** (0.05)	0.53*** (0.07)	0.53*** (0.06)	0.52*** (0.07)	0.37*** (0.06)	0.44*** (0.06)	0.49*** (0.06)	0.51*** (0.07)
Observation	42	42	42	42	42	42	42	42
Variables included in first- and second-stage regressions								
Covid_19	0.10*** (0.01)	0.10*** (0.01)	0.09*** (0.01)	0.10*** (0.01)	0.11*** (0.01)	0.11*** (0.02)	0.10*** (0.01)	0.10*** (0.01)
Log (Averaged bank concentration)		−0.34*** (0.08)	−0.32*** (0.09)	−0.25*** (0.09)	−0.11 (0.09)	−0.13 (0.21)	−0.15 (0.21)	−0.15 (0.22)
Log (Averaged bank overhead)			−0.11 (0.10)	−0.08 (0.09)	−0.05 (0.06)	−0.02 (0.07)	−0.01 (0.07)	0.01 (0.07)
Log (Rule of Law)				0.26** (0.11)	0.39*** (0.09)	0.39*** (0.08)	0.32*** (0.08)	0.36*** (0.12)

(continued on next page)

Table A6 (continued)

	1	2	3	4	5	6	7	8
Log (Urban population)					−0.09*** (0.04)	−0.09*** (0.02)	−0.09*** (0.02)	−0.09*** (0.02)
Log (Financial Account)						−0.01 (0.09)	0.07 (0.14)	0.08 (0.15)
Log (Debit Card)							−0.06 (0.09)	−0.08 (0.09)
Log (Foreign Direct Investment)								−0.01 (0.01)
Constant	−1.28*** (0.20)	−0.22 (0.32)	−0.12 (0.29)	−0.29 (0.27)	−0.62** (0.31)	−0.55 (0.65)	−0.55 (0.62)	−0.58 (0.70)

(¹): Values in parentheses refer to the clustered standard errors estimated at the country level; (a): refers to the Cragg–Donald Wald F statistic and (b) to the Kleibergen–Paap rk Wald F statistic. Both statistics are compared to the critical values of Stock and Yogo. For K1 = 1 and L1 = 1 (one endogenous regressor), the Stock and Yogo critical values are 16.38, 8.96, 6.66, and 5.53 corresponding to 10%, 15%, 20%, and 25% maximal IV size, respectively, the bias percentages that are acceptable for IV estimator. + + +: Statistically significant at all critical values of Stock and Yogo. ***, **, and *: denote significance at the 1%, 5%, and 10% levels, respectively.

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