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The Influence of Financial Inclusion on Gross National Income in East African Countries: A Dynamic Multivariate Bayesian Structural Model Approach

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Abstract
East Africa's slow economic growth is due to complex issues driven by a combination of factors, including a high debt burden, political instability, conflict and violence, climate change impacts, inadequate infrastructure, and an underdeveloped financial services sector. For these countries, financial inclusion research is crucial because it highlights how increasing access to affordable, responsible financial services empowers individuals and businesses, reduces poverty and inequality, and enables progress towards sustainable development goals. In particular, formal financial inclusion is currently a policy priority worldwide due to its effects on the rapid mobilization of financial resources, the efficient allocation of productive inputs, and the reduction of the dependence of small businesses and households on expensive credits from informal economic sectors. The study uses the dynamic multivariate panel data models to analyze the impact of a multidimensional financial inclusion index on per capita gross national income among East African Countries. The study's results demonstrate that indicators of human development are key drivers of financial inclusion growth as they enable greater access to and usage of financial services. Countries such as the DRC and Burundi should focus on providing basic financial services. Tanzania, Rwanda, and Kenya must focus on the overall improvement of financial inclusion. Due to the long-term effects of financial inclusion on gross national income, East African countries are likely to benefit more from policies that support sustained investment in more inclusive and comprehensive financial systems.
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1. Introduction

Since the United Nations Capital Development Fund (UNCDF) started supporting microcredit institutions in the 1990s, financial inclusion has garnered significant interest, driven by research findings that underscore its strong correlation with increased economic growth and development. According to Sutton & Jenkins (2007), the global recognition of the pivotal role of financial inclusion in national income growth has also underscored the potential contribution of the financial sector to overall economic welfare improvement and business formation. Notable studies by Honohan (2008), Bhatia & Chatterjee (2010), Kempson & Collard (2012), Naih, Jabbouri & Helmi (2023), and Amaliah et al. (2024) have further reinforced this understanding. Demirguc-Kunt et al. (2015) and Demirgüç-Kunt, Klapper & Singer (2018) suggest that improved financial inclusion implies that many economic agents utilize the formal financial sector to settle payments, save, and obtain affordable loans. These studies also demonstrate that financial inclusion enables households and businesses to smooth their consumption and manage income shocks, thereby promoting economic growth. It pools resources into the financial sector through savings that fund physical and human capital, a prerequisite for economic growth.

Financial inclusion is a multifaceted concept, as evidenced by proposed definitions from various scholars, including Sarma (2008), Bhatia and Chartlejee (2010), Jima & Makoni (2023), and Siddiki & Bala-Keffi (2024). The World Bank defines financial inclusion as the "means people and businesses have easy access and affordable financial products and services that meet their needs - transactions, payments, savings, credit and insurance services - delivered responsibly and sustainably." Other definitions emphasize the ease with which economic participants access, use, and avail themselves of formal financial services at lower cost. Formal financial institutions include bank branches, bank deposits, and credit. The definition implies that when financial inclusion is low, economic agents are unable to access financial products and services, which negatively affects national income, economic growth, and development. Research indicates that enhanced financial inclusion holds significant potential for boosting national income, offering a promising future for the global economy and entrepreneurship. Moreover, various studies, including Park & Mercado (2018), Khan et al. (2022), Atadouanla et al. (2024), and Tabash et al. (2024), show that financial inclusion is the driving force that can stimulate and enhance inclusive economic growth and development by reducing poverty and socioeconomic inequities and stabilizing the global financial systems.

The East African Community (EAC) member countries[i] have recognized the potential of financial inclusion (Rwigema, 2022). The EAC website at https://www.eac.int/overview-of-eac indicates that in the East African Community, "people experiencing poverty hamper national income and development as they cannot invest their inadequate savings nor receive loans to increase consumption." The EAC's mission is to "widen and deepen economic, political, social, and cultural integration to improve the quality of life of the people of East Africa through increased competitiveness, value-added production, trade, and investment." Moreover, one of the components of the EAC Financial Sector Development and Regionalization Project (EAC, 2025) is to broaden and deepen the financial sector by establishing a single market in financial services among the EAC Partner States. The primary objective is to capitalize on the EAC single market's scale by offering a broader range of affordable formal financial services and products to a more diverse client base, including underserved communities.

At the country level, while Kenya started the financial inclusion program in 2005 as a means to stimulate wealth creation and reduce poverty (GRK, 2007), reports by UNDP (2013), Fernando et al. (2018), Abdi, M. (2022), NCFFI (2023), and Uganda (2023), indicate that other EAC members countries started late under various economic development programs: Burundi (2014), the Democratic Republic of Congo (2019), Rwanda (2012), Somalia (2024), the Republic of South Sudan (2013), Tanzania (2013), and Uganda (2017). All member countries have launched the National Financial Inclusion Frameworks, a significant initiative to enhance access and usage of affordable, high-quality financial products and services. The framework aims to increase the percentage of adults who access formal financial services and grow the usage of formal financial products. These initiatives are at various stages of implementation. Somalia and the Republic of South Sudan were excluded from this study due to substantial non-random missing data, particularly for the determinants of the financial inclusion variables.

This study employs Sarma's (2008) distance approach to calculate a composite financial inclusion index that is comparable across countries. When constructing the index, there is no requirement to specify weights a priori. The aggregate index offers a straightforward method for monitoring overall changes in financial inclusion, enabling statistical tools to assess the current state and track historical trends. The study also investigates the nexus between financial inclusion and national income in the EAC member states. Due to unobserved individual-specific heterogeneity and lagged dependent variables, which are ubiquitous in macroeconomic variables, Hsiao (2014) observed that the dynamic panel data model produces unbiased and efficient estimates. Since panel data tracks observations of individual countries over multiple periods, it reveals dynamic patterns in both cross-sectional and time-series frameworks. According to Moral-Benito, Allison & Williams (2019), panel data accounts for temporal dependencies by including the lagged dependent variable as a regressor, providing a more accurate representation of the dynamic nature of macroeconomic variables. The panel data accounts for historical performance and state dependence, thereby measuring the effect of exogenous variables on dependent variables based on their past values.

The dynamic multivariate panel data models (DMPMs) introduced by Helske & Tikka (2024) allowed for the estimation of the causal effect of financial inclusion on the per capita national gross income (GNI). According to the World Bank Definition, "GNI is the sum of value added by all resident producers plus any product taxes (less subsidies) not included in the valuation of output plus net receipts of primary income (compensation of employees and property income) from abroad." It measures the total earnings of all the country's residents at a given price. The World Bank employs the "Atlas method" to convert GNI figures from local currency to U.S. dollars, thereby mitigating exchange rate fluctuations and providing a more accurate comparison between countries. According to the World Bank's Country and Lending Groups, in 2022, the GNI per capita for lower-income economies was below $1,136. Lower-middle-income economies were those with a GNI per capita between $1,136 and $4,465; upper-middle-income economies were those with a GNI per capita between $4,466 and $13,845, and high-income economies were those with a GNI per capita greater than $13,846.

The adapted analytical tool explains financial inclusion responses to policy innovations related to idiosyncratic, country-specific, and composite shocks while addressing endogeneity and simultaneous causality regarding financial inclusion and national income responses. Moreover, the existing literature on financial inclusion identifies interest rates (Miller, 2013), literacy rates (Gautam, Rastogi, & Rawal, 2022), and concentration of the informal production sector (Farazi, 2014) as drivers of financial exclusion. This research includes other factors to inform policymakers in the EAC member states regarding formulating practical and inclusive FI policies that improve the economic welfare of all people.

The study's contribution is threefold. The study fills the literature gap in the relationship between financial inclusion and national income in East Africa. The study also examines the factors influencing financial inclusion and their dynamic relationship with national income, while also considering the potential reverse causality from national income to financial inclusion. The hypothesis is that while financial inclusion Granger causes (Granger, 1988) an increase in national income, there is also a reverse causality (Antonakis et al., 2014) of national income on financial inclusion. That is, while financial inclusion impacts national income, based on established economic theory, there are demand- and supply-side variables that determine financial inclusion, as summarized by Barik & Lenka (2022). Since increasing national income is a prerequisite for ensuring greater financial inclusiveness, there is a reverse causality between financial inclusion and national income, as well as between national income and financial inclusion. The DMPM's empirical model applied in this study accounts for this theoretical background to produce efficient and unbiased results. Following the brief introduction, the paper consists of four additional sections. Section two presents theoretical and empirical literature on FI and discusses methodology. The results are presented and discussed in Section 3, and Section 4 concludes the paper.

2. Literature Review

2.1 Multidimensional index of financial inclusion

At the micro and macro levels, as defined by Sarma and Pais (2011), "FI indicators measure access, usage, and quality of available financial products and services." The access indicators measure the reach of financial services, such as the number of bank branches or point-of-sale devices. They also measure demand-side barriers, such as the cost or information required to access financial institutions. The usage indicators measure how clients utilize financial services, including the average savings balances, the number of transactions, and the number of electronic payments made. The quality indicators measure the quality of the products and the delivery service. In literature, critical socioeconomic barriers to the usage and quality of financial inclusion are the urban population (Babajide et al., 2021), financial education (Van et al., 2021), economic stability (Jima & Makoni, 2023), and unemployment (Matekenya, Moyo, & Jeke, 2021). The barriers prevent people from opening an account in financial institutions due to high account fees, stringent documentation requirements, long travel distances, and legal hurdles, as discussed by Kaliba, Bishagazi & Gongwe (2023).

Kempson, Atkinson & Pilley (2004) reviewed the early policy-level responses to financial exclusion in developed economies. Leyshon & Thrift (1995) provide early definitions of financial inclusion as the processes that facilitate economic agents' access to the formal financial system. While some definitions emphasize access and affordability (Demirguc-Kunt et al., 2015), others focus on access, availability, and usage (Demirguc-Kunt et al., 2018) in building an inclusive financial system. Since individual indicators cannot adequately capture the extent of financial inclusion, most researchers construct a weighted comprehensive measure that aggregates the sub-indicators into a financial inclusion index, as in Cámara and Tuesta (2014) and Goel and Sharma (2017). Additionally, Sarma (2008) and Sarma & Pais (2011) demonstrate that analyzing only the financial inclusion sub-indicator provides partial information, leading to potentially misleading interpretations. They suggest constructing a comprehensive, single-number measure that aggregates all aspects of financial inclusion sub-indicators to create an index of multidimensional financial inclusion.

A single-number index has several advantages, as highlighted by Sarma (2008), and Cámara & Tuesta (2014). First, indices summarize complex, multidimensional phenomena, such as financial inclusion. Second, they reduce the size of a set of individual metrics without losing the underlying information. Third, they are also easier to interpret than multiple indicators. Fourth, they enable effective comparison of complex dimensions. Finally, they provide a synthetic measure of a country's relative performance and progress in achieving a policy goal, such as financial inclusion. Therefore, the constructed index enables the comparison of financial inclusion levels within and across economies at a particular time, facilitating the monitoring of policy initiatives, and allows for the use of established statistical tools to answer research questions regarding financial inclusion. When constructing the index of India, Gupte, Venkataramani & Gupta (2012) indicate that an excellent aggregate measure should encompass many dimensions of financial inclusion, be easy and straightforward to compute, and be comparable across countries.

The practical approaches to constructing the index include the max-min approach and the use of distance functions. The root of the maxi-min approach lies in the United Nations Development Program (UNDP) methodology, which combines various socioeconomic indicators to compute the Human Development and Gender Empowerment Indexes, as seen, for example, in Lind (2019). The UNDP approach transforms the minimum value into zero and the maximum value into one for every indicator and converts any other value into a decimal between zero and one. The final index aggregates the normalized dimension using simple arithmetic or geometric averages. Bardhan & Klasen (1999) nd Dijkstra (2002) discuss the limitations of this approach. Although the max-min approach normalizes the index to be between 0 and 1, the critical limitation is the assumption of perfect substitutability. All sub-indicators/dimensions are supposed to be equally important when computing the index. Notably, Vafaei, Ribeiro & and Camarinha-Matos (2022) prove that if there is an increase in one sub-indicator and a decrease in any other sub-indicator by an equal magnitude, the max-min approach counterweighs the impact.

The distance-based technique proposed by Sarma (2008) draws inspiration from the max-min approach to estimate the index. Then, it uses the inverse Euclidean distance function to aggregate the normalized dimensions into a multidimensional scale. The distance-based index is calculated in two steps as follows:

$$FIN_{i,s} = (FI_{i,s} - \min(FI_{i,s})/\max\,(FI_{i,s} - \min(FI_{i,s}). \tag{1.1}$$

$$MFII_i = 1 - \left(\sqrt{\sum_{s=1}^{S}(1 - FIN_{i,s})^2 \Big/ S}\right). \tag{1.2}$$

The Expression (1.1) in Equation (1) represents the max-min approach that normalizes each of the sub-indicators ($FI_{i,s}$), to normalized sub-indicators ($FIN_{i,s}$). For each observation *i:(i=1,.., n)*, n is the number of observations in the sample. Expression (1.2) aggregates the normalized sub-indicators to a multidimensional financial index ($MFII_i$) where S is the number of indicators. The MFII ranges from 0 to 1. Shah & Ali (2023) categorize it as follows: 0 to 0.30 (low financial inclusion), 0.31 to 0.50 (medium financial inclusion), and 0.51 to 1 (high financial inclusion). Apart from normalization, the aggregated index in expression 1.2 satisfies several desirable properties, including symmetry, monotonicity, proximity, uniformity, and signaling on the level of financial inclusion for comparative purposes. See Sinha (2014), Park & Mercado (2018), Ghosh & Sahu (2021), and Li & Wang (2023), among others, who have applied Sarma's (2008) approach in the financial inclusion literature. For Expression (1.2), some researchers, such as Li & Wang (2013), suggest using the Mahalanobis distance function or different weights to reflect the importance of each sub-indicator when estimating the index. However, as shown by Brereton & Lloyd (2016), the Mahalanobis distance is designed to capture linear relationships between variables. It may not accurately represent distances in datasets with complex, non-linear relationships.

2.2 Causality and endogeneity of financial inclusion on economic growth

Most studies examining the causal relationship between national income and financial inclusion across countries use the dynamic panel model for data analysis.[ii] These models aim to integrate variations within and between countries to provide unbiased estimates for time-invariant variables and investigate heterogeneity to determine how economic countries adjust to changes over time. In addition, according to Abonazel (2017), the dynamic panel models avoid aggregation biases that obscure underlying economic shocks and produce generalized results as discussed by Rzayev & Samoilikova (2020). The latter is critical when the objective is to provide policymakers with policy insights or when formulating public policies to support efficient and inclusive financial systems. There are various approaches when estimating causal dynamic panel models. Mulder & Hamaker (2021) demonstrate the application of dynamic panel data models with fixed effect and dynamic structural equation models, cross-lagged panel models (CLPM), and their various extensions. Zyphur et al. (2020) present the application of a general cross-lagged panel model in a structural equation modeling framework. Bailey & Katz (2011) discuss the panel-corrected standard error (PCSE) model.

In the presence of time-invariant variables, studies by Littlefield et al. (2022) and Lucas (2023) show that the autoregressive relationships of CLPM and PCSE models fail to represent relationships across and over time, which leads to erroneous conclusions regarding the presence, predominance, and signs of causal influences. These results suggest that studies on the relationship between financial inclusion and national income are of both theoretical and empirical interest and require further research grounded in economic theory and empirical models. Schumpeter (1911) pioneered the finance and growth theory, which was expanded later by other scholars, including Gurley & Shaw (1955), King & Levine (1993), among others. The theory suggests a dynamic, productive environment built through the supply-leading and demand-following framework. It asserts that income inequality and slackened national income growth emanate from a lack of access to financial resources. Thus, fast national income is achievable through easy access to affordable finance. Therefore, financial inclusion is a vehicle for increased participation by integrating all economic agents into the financial sector.

Under the finance and growth theory, the financial sector is considered essential in facilitating economic growth. According to Patrick (1966), there are three ways in which financial inclusion influences national income: financial intermediation, which changes ownership of assets; the existence of institutions that facilitate transfer and the increase in capital accumulation of funds and efficient allocation of resources to more productive uses; and increased savings and capital accumulation. Gul, Usman & Majeed (2018) demonstrate that intermediation affects national income by increasing the velocity of money and removing impediments for those with limited access to finance. It directly increases access to finance, indirectly contributing to increased national income and consumption (Sethi & Acharya, 2018) and through the financial intermediation process (Siddiki & Bala-Keffi, 2024).

The extensive empirical literature supports that financial inclusion and national income are positively related. Various studies cover specific countries and regions, use different approaches and time frames, and analyze different aspects of financial inclusion. The most recent studies include those by Labella-Fernández, Serrano-Arcos & Payán-Sánchez (2021), who found that financial inclusion has a positive impact on firm growth, as well as Gul et al. (2020), whose study findings suggest that financial inclusion reduces inequality. Using cross-country data from 44 emerging markets and 153 countries globally, Emara & El Said (2021) and Siddiki & Bala-Keffi (2024), respectively, concluded that financial inclusion has a positive impact on economic growth, and the extent of this impact depends on the level of development. Meshashi & Makoni (2023) also apply cross-country data to estimate the effects of national income in Sub-Saharan Africa, suggesting a long-run relationship between financial inclusion and national income.

Gourène & Mendy (2017) also found a positive causality between financial inclusion and economic growth in a study covering West African Economic and Monetary Union (WAEMU) countries. Furthermore, a study in Nigeria by Adedokun & Aga (2021) and Stephen & Wakdok (2020) yielded findings suggesting a positive relationship between financial inclusion and national income. A study by Bigirimana & Hongyi (2018), Amaliah et al. (2024), Rahman, Chowdhury & Sristi (2024), and Odame, Appiah & Gyimah (2024) also confirmed the positive impact of financial inclusion on economic growth in Rwanda, Indonesia, and Bangladesh, respectively. Studies that have found a negative correlation between financial inclusion and economic growth, among others, include Kapingura, Mkosana & Kusairi (2022) in the Southern African Development Community countries, Seven and Yetkiner (2016) in high-income countries, and van Wyk and Kapingura (2021) in South Africa.

A thematic review by Ozili, Ademiju & Rachid (2023) concluded that most (few) studies report a positive (negative) impact of financial inclusion on economic growth. Access to financial products and the quality of financial services were the main critical channels through which financial inclusion affects economic growth. While these studies employed varying sub-indicators of financial inclusion and national income proxies, dissimilarities in empirical methodologies, particularly regarding causality tests, cointegration, and regression techniques, partly explain the conflicting results. They also concluded that these studies should have used relevant theories when modeling the impact of financial inclusion on economic growth.

For cross-country studies presented, the traditional method includes variants and extensions of fixed-effects and random-effects panel models, hypothesizing that a change in financial inclusion produces a shift in economic growth while holding all other economic variables constant. These growth panel models include the financial inclusion variables or index as a shift variable with other control variables. The assumption implies that financial inclusion varies randomly and independently from the economic system, see, for example, Ifediora et al. (2022). However, financial inclusion depended on some other variables in the economic system, hence the endogeneity problem. A bi-directional causal relationship (simultaneity) between national income and financial inclusion also necessitates the use of Pearl's (2012) structural causal models, as presented in Figure 1.

Figure 1: Causal Graph on the Relationship between National Income, Financial Inclusion, and Associated Potential Covariates

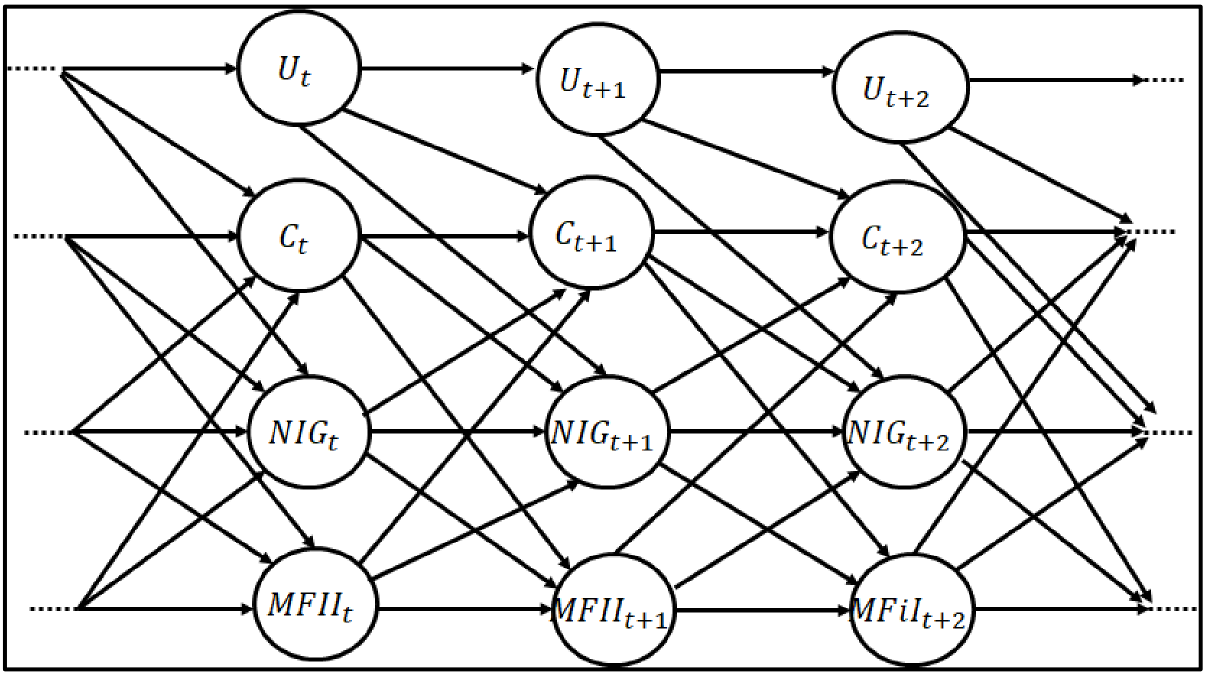


Figure 1 presents a graphical simplification of the SCM model adapted from Helske & Tikka (2024). The objective is to estimate the impact of multidimensional financial inclusion ($MFII_{t+k}$) on national income (NIG_{t+k}) while accounting for additional covariates (C_t) and unobserved time-varying confounders (U_t) that affect national income. The SCM model in Figure 1 identifies cause-and-effect relationships, predicts outcomes, and generalizes findings to new scenarios. Arrows in Figure 1 correspond to the direct causal effects at times *t*, *t + 1*, and *t + 2*, and each edge links to the regressive and auto-regressive, which can be either time-invariant or time-varying effects of data point (t) on (t+1) or (t+1) on (t+2). For simplicity, the graph does not display time-invariant unobserved and exogenous variables, lagged values, or any model parameters, as there are no parametric assumptions about the distributions of each variable. Helske & Tikka (2024) show that if the graph structure does not depend on time (*t*), the causal effect of financial inclusion is identifiable and estimable.

Note that the structure of Figure borrows from the cross-lagged panel model formulation of Allison et al. (2017). With two response variables, that is, national income ($NGI_{i,t}$) and financial inclusion ($MFII_{jt}$), the time point (t) here is needed to model how $MFII_{jt}$ depends on NGI_{jt} and estimate the effect of $MFII_{jt}$ on NGI_{jt}. Specifically, as Helske & Tikka (2024) show, the DMPM supports multiple interdependent responses where the causal effect is a function of time. It is a joint model that captures the complex feedback dynamics illustrated in Figure 1 and estimates time-dependent short-term and long-term causal effects by applying Bayesian techniques. The model also accounts for additional covariates (C_t), and unobserved time-varying and time-invariant confounders (U_t). These considerations are particularly relevant, as changes in a country's monetary policies can significantly impact the short- and long-term trajectories of financial inclusion and economic growth.

3. Data and Empirical Model

3.1 Multidimensional financial inclusion index and determinants

This study employs the Sarma (2008) and Gebregziabher and Makina (2015) approach, as outlined in Equation (1), to construct a multidimensional financial inclusion index from sub-indicators that measure access, usage, and the quality of products and services. The data is from the International Monetary Fund's Financial Access Survey (FAS)[iii]. To achieve target 8.10 of the Sustainable Development Goals, the United Nations uses the number of ATMs and the number of commercial bank branches per 100,000 adults as critical indicators of financial inclusion (World Bank, 2021). The two indicators represent access (i.e., physical point services) to improve financial services for everyone, presenting the foundation of financial inclusion indicators. However, the Group of Twenty (G-20)[iv] Member countries expanded the indicators of financial inclusion to nine (GPFI, 2016). In addition to the two sub-indicators that measure access, the G-20 has also added other indicators to measure the usage and quality of financial services.

The usage indicators are the number of deposit accounts at commercial banks per 1,000 adults, the number of loan accounts with commercial banks per 1,000 adults, the number of life and non-life insurance policyholders per 1,000 adults, deposit accounts of SMEs at commercial banks (as % of non-financial corporations), and loan accounts of SMEs at commercial banks (as % of non-financial corporations). The quality of financial services indicators includes the number of registered mobile money agent outlets per 100,000 adults and mobile money transactions per 100,000 adults. For East African Countries, data on deposit accounts and loan accounts of SMEs at commercial banks, as well as the number of life and non-life insurance policyholders, had substantial missing values and were excluded from the study. For usage, we include the number of borrowers from commercial banks (per 1,000 adults) to substitute for the missing data.

Regarding the determinants of financial inclusion in developing countries, the literature on demand-side measures of financial inclusion identifies economic status, social identity, educational training, and cultural/religious characteristics as the leading explanatory variables driving the supply of financial inclusion sub-indicators. See, for example, Fungáčová & Weill (2016), Zins & Weill (2016), Yangdol & Sarma (2019), and Nsiah & Tweneboah (2023). In these studies, however, statistically significant variables tend to capture sub-indicators of the United Nations Development Programme's (UNDP) Human Development Index (HDI) as presented by Sagar & Najam (1998). The HDI is a summary measure of a country's average achievements in three fundamental aspects of human development: health (determined by life expectancy at birth), knowledge (assessed by education regarding mean years of schooling for adults and expected years of schooling for children), and standard of living (measured as gross national income per capita). Apart from other control variables explained in the following section, we used the sub-indicators of HDI as critical determinants of financial inclusion in this study.

3.2 Multivariate dynamic panel data model

The critical data for the multivariate dynamic panel data model are from the World Bank's World Development Indicators Database. Addition data were from the United Nations Conference on Trade and Development (UNCTAD) data center (trade and foreign direct investment data), the Organization for Economic Cooperation and Development (OECD) data explorer (the flow of foreign aid and assistance), and the Internation Labor Organization (ILO) statistics data tools (labor force participation)[v]. Quantitatively, and based on Equations (4) and (5), the study quantifies the causal effects of financial inclusion on each country's national income per capita by adapting the DMPMs of Helske & Tikka (2024. Due to unobserved country-specific heterogeneity, the panel specification of the empirical model is:

$$MFII_{i,t} = \tau_{t,11}NIG_{i,t-1} + \tau_{t,12}MFII_{i,t-1} + \beta_{11}LEP_{i,t} + \beta_{12}EYS_{i,t} + \beta_{13}MYS_{i,t} + \sum_{j=4}^{M}\beta_{1j}C_{ji,t} + \vartheta_{1i} + \delta_{1t} + \vartheta_{1i} * \delta_{1t} + \varepsilon_{1i,t}, \quad 2.1$$

$$NIG_{i,t} = \tau_{t,21}MFII_{i,t-1} + \tau_{t,22}NIG_{i,t-1} + \sum_{k=1}^{K}\beta_{k2}A_{ki,t} + \vartheta_{2i} + \delta_{2t} + \vartheta_{2i} * \delta_{2t} + \varepsilon_{2i,t.} \quad 2.2$$

In Equation (2), MFII is the aggregated multidimensional financial inclusion index from Equation (1) using the UNDP standard and G-20 indicators, and *NIG* is the gross national income per capita at the 2015 constant in U.S. \$. The subscripts *1* and *2* represent channel 2.1 and 2.2, respectively; the subscripts *i* and *t* denote country and year, respectively. For brevity, the omission of the subscripts for each observation in the sample helps to avoid cluttering. The explanatory variables *LEP, EYS*, and *MYS* in Expression (2.1) denote life expectancy at birth, mean years of schooling for adults, and expected years of education for children, respectively. The three variables are indicators of the Human Development Index. Additionally, the subscripts j ($j = 4, ..., M$) and k ($k = 1, ..., K$) represent the number of control variables (M) for financial inclusion and national income (K), respectively. Furthermore, the parameters (τ) and (β) represent the estimated effect of the response variable in the past on the current value of the channel (i.e., either $MFII_{i,t}$or $NIG_{i,t}$) and time-invariant regression coefficients. By jointly estimating both channels of Equation (2), the country-specific fixed effect (ϑ), time-varying coefficients (δ), and country-specific time trends ($\vartheta * \delta$) control for unobservable heterogeneity across countries and time. The period is from 2009 to 2022.

Apart from HDI sub-indicators, we used the available literature to select other macroeconomic control variables influencing financial inclusion, that is ($C_{ji,t}$) in channel (2.1). For the global model, the included variables were inflation, unemployment rates, and the percentage of women aged 15 and older who are economically active, as discussed by Gebrehiwot & Makina (2019). Other macroeconomic variables considered by Pandey, Kiran & Sharma (2022) included broad money (as a percentage of GDP) as a measure of deposits, the percentage of the population with internet access, and population density. The financial literature shows that these macroeconomic variables aggregate reasons (i.e., demand-side) for why individuals or households use or fail to use formal financial services. In other words, they are drivers of financial inclusion supply; they minimize involuntary financial exclusion by removing barriers and promoting the actual use of formal financial services at the macro level.

For channel (2.2), studies that review the determinants of national income in developing countries ($A_{ki,t}$), include Petrakos & Arvanitidis (2008) and Chirwa & Odhiambo (2016), who identified critical control variables as inflation, unemployment rate, foreign aid and assistance inflow, net foreign direct investment (inward-outward), government investment (gross capital formation at constant price), trade (net export=imports-export), demographics (population density), and natural resources base, in which we use the value added of agriculture, forestry, and fishing as a percent of GDP. Moreover, reviews by Vu, Hanafizadeh & Bohlin (2020) and Stoica, Roman & Rusu (2020) demonstrate that information and communication technology (ICT) and entrepreneurship are also crucial factors influencing economic growth. For this study, we used the percentage of individuals using the internet (as a proportion of the population) and the number of new business registrations (new registrations per 1,000 people aged 15-64) to measure IT and entrepreneurship, respectively.

Note that the country- and time-fixed effects in Expression (2.2) capture the impact of other variables, such as fiscal policy, monetary policy, and regional, political, and financial factors commonly included when modeling factors that influence national income and economic growth. These control variables included in Expression (2.2) are a mix of Solow's growth model (Solow, 1988), emphasizing the importance of investment, population growth, and technological progress, and the neoclassical growth models of Romer (1989), which posit that human capital and innovation capacity drive national income. To estimate Equation (2), Tikka & Helske (2023) suggest using a multivariate joint model accounting for time-varying variables using splines and time-invariant effects. The method also enables the evaluation of long-term counterfactual predictions, considering the model's dynamic structure through efficient simulation of the posterior predictive distribution.

Based on Figure 1, apart from assessing the dynamic and reverse causality, the lags in Equation (2) allow temporal information flow from improvement in financial inclusion to economic growth. As Sahay et al. (2015) demonstrate, analysis is crucial for understanding how changes in financial inclusion impact economic growth, identifying trends, and uncovering potential public policy and investment opportunities to enhance the effect of financial inclusion on economic growth. To estimate Equation (2), Tikka and Helske (2023) present a dynamite package in the R software environment (R Team, 2023) for calculating the short- and long-term direct causal effects using Equation (2). For this study, the package facilitated the efficient computation of country-level and time-fixed impact, as well as predictions over time. It also offered a comprehensive suite of visualization and model diagnostics tools to produce efficient and unbiased results. Since the financial inclusion (MFII) has to be within the open interval (0, 1), the estimated values did not include zero and one as part of the data points to qualify as a beta distristribution (McDonald & Xu, 1995); therefore, for both channels 1 (expression 2.1) and channel 2 (expression 2.2) were fitted as Gaussian.

Note that in Equation 2, it is possible to estimate two model categories. The first category comprises two response variables (i.e., MFII and GNI), country-specific random effects, time-varying intercepts, and a first-order lag of MFI and GNI, along with a list of time-invariant covariates. The model implies that each country has a unique, unobserved effect, considered a random variable, drawn from a larger population of possible group effects. The second category model had a similar structure but included time-varying effects of the first-order lag for MFII and GNI. The model suggests that the relationship between the response variables and the first-order lag of MFII and GNI evolves over time and across countries.

Pareto k diagnostic proposed by Vehtari, Gelman & Gabry (2017) is applied to select the best model for prediction purposes. It is a statistical tool used to assess the reliability and validity of estimates derived from importance sampling, specifically, Pareto Smoothed Importance Sampling (PSIS), particularly in the context of Leave-One-Out Cross-Validation, as suggested by Vehtari et al. (2024) in Bayesian inference. It is essentially a measure of the stability and reliability of the sampling weights for each observation in the dataset. PSIS utilizes the generalized Pareto distribution to model the tail of the distribution of importance weights. The shape parameter, denoted by 'k', determines the tail behavior of this distribution, and $k < 0.7$ (good) indicates a well-behaved tail with finite variance, and the estimates are generally dependable. For $0.7 < k < 1$ (bad), the variance of the importance ratios is infinite, but PSIS can still provide reliable estimates. However, the convergence of estimates may be slower. For $k \geq 1$ (very bad), the mean of the importance ratios may not exist, and PSIS estimates can become unreliable, with potentially significant bias and slow convergence.

The PSIS diagnostic plots are tools for visualizing these k-values for each observation (or group of observations) in the dataset. By examining the distribution and magnitude of k-values in the plot, one can identify observations that may be unduly influencing the PSIS estimates. The plots of the estimated effective sample size (ESS) supplement the results and quantify the reliability and informativeness of the posterior samples. The plots indicate how much independent and identically distributed data would be needed to achieve the same level of uncertainty using the current sample. Higher ESS values suggest more reliable estimates. Consult Vehtari, Gelman & Gabry (2017) and Vehtari et al. (2024) for details.

4. Results and Discussion

4.1 Statistics of dependent and independent variables and potential influence

Table 1 presents the summary statistics of the variables used to compute the financial inclusion index, the estimated multidimensional financial inclusion index, and the per capita income value for all countries in 2009 and 2022. The variables related to access to financial services were the number of automated teller machines (ATMs) and commercial bank branches per 100,000 adults. The average number of automated teller machines (ATMs) per 100,000 adults was 4.97, with the lowest in Burundi (1.25) and the highest in Kenya (8.73), which is relatively low even by African standards. The number of ATMs varies significantly, depending on the level of economic development and the degree of financial access. According to the available World Bank (2004/2022), the range is between 60 and 80 per 100,000 adults for developed countries in Europe, North America, and Asia, with the highest concentration in Macao. For the third quartile in African countries, the average is around 18 ATMs per 100,000 adults, with the highest being 93 ATMs per 100,000 adults in Seychelles. Worldwide, the average number of ATMs per 100,000 adults ranges from 3 to 6 ATMs in low-income countries and Sub-Saharan Africa, respectively (Maino et al., 2019). It is essential to recognize that commercial bank branches serve as key indicators of financial inclusion, as they represent a crucial aspect of access to formal financial services, particularly in areas where digital financial services may be limited or unavailable.

For the study period, as presented in Table 1, the number of ATMs per 100,000 adults averaged 3.36, with the lowest value (1.87) in the Democratic Republic of the Congo (DRC) and the highest value (5.22) in Rwanda, followed by Kenya (5.06). High-income countries typically have significantly more ATMs per 100,000 adults, with an average of around 85. The number of commercial banks per 100,000 adults was higher in Rwanda (5.22) and lowest in Burundi (2.89), with an average of 3.36 branches per 100,000 adults in the region. Comparatively, data from the World Bank's Global Financial Development database show that the average number of commercial bank branches per 100,000 adults in Sub-Saharan Africa is approximately 4.06 establishments, with a slight decline over the past few years. In high-income countries, the rate is approximately 20 per 100,000 adults (Beck et al., 2023). The same data also show that in 2021, Saudi Arabia had the highest number of commercial bank branches per 100,000 adults, at 1,501.22, followed by Sweden (224.79) and Trinidad and Tobago (176.95). The average for 2021, based on 46 high-tier countries, was 60.7 bank branches per 100,000 adults; the lowest value was in Palestine at 0.52 bank branches per 100,000 adults. The depth of outreach for financial products and services was relatively low compared to high-income countries, but better than in other countries in Sub-Saharan Africa and low-income countries. The number of ATMs is a crucial indicator of financial inclusion, as they serve as physical access points to formal financial services, particularly for individuals and communities in underserved areas.

Table 1. Indicators of Financial Inclusion and Economic Growth

Indicators of financial inclusion and economic growth	Burundi	DRC	Kenya	Rwanda	Tanzania	Uganda	Average
Access: the depth of outreach of financial products and services							
Number of ATMs per 100,000 adults: Mean	1.25	5.8	8.73	4.25	5.59	4.19	4.97
Standard Deviation	0.46	4.77	1.13	1.56	1.02	0.46	1.57
Number of commercial bank branches per 100,000 adults: Mean	2.89	1.87	5.06	5.22	2.43	2.7	3.36
Standard Deviation	0.41	1.34	0.43	0.98	0.28	0.28	0.62
Usage: how clients use financial products and services							
Number of deposit accounts at commercial banks per 1,000 adults: Mean	27.00	62.00	1,314.00	351.00	126.00	350.00	371.67
Standard Deviation	18.00	49.00	643.00	145.00	177.00	176.00	201.33
Number of loan accounts in commercial banks per 1,000 adults: Mean	11.20	9.36	241.00	26.40	57.10	39.50	64.09
Standard Deviation	3.90	4.50	116.00	15.80	54.30	19.50	35.67
Number of life and non-life insurance policy holders: Mean	45,000	62,900	1,701,000	377,000	349,000	402,000	489,483
Standard Deviation	13,800	22,600	677,000	156,000	147,000	192,000	201,400
Number of borrowers from commercial banks per 1,000 adults: Mean	11.20	5.35	217.00	29.70	51.40	36.70	58.56
Standard Deviation	5.43	3.93	123.00	22.90	52.30	19.90	37.91
Quality: Clients are aware, understand, and the services meet their needs							
Number of active mobile money agent outlets per 100,000 adults: Mean	1,018	86	732	395	633	672	589.25
Standard Deviation	742	67	163	228	237	149	264.32
Number of registered mobile agent outlets per 100,000 adults: Mean	26	375	1,300	1,060	1,632	879	878.60
Standard Deviation	15	90	581	773	787	484	455.00
Number of mobile money transactions per year per 1,000 adults: Mean	73	9,881	41,699	41,971	37,609	64,695	32,655
Standard Deviation	57	3,910	20,616	51,614	21,354	63,609	26,860
Indicators of financial inclusion and economic growth							
Multidimensional financial inclusion index (IMF):Mean	0.677	0.525	0.546	0.670	0.602	0.467	0.581
Standard Deviation	0.311	0.252	0.330	0.295	0.283	0.302	0.296
Multidimensional financial inclusion index (G20): Mean	0.418	0.486	0.413	0.373	0.347	0.350	0.398
Standard Deviation	0.176	0.266	0.200	0.195	0.181	0.203	0.204
National Income per Capita (US 2015 $): Mean	276.66	423.47	1,417.31	726.42	929.10	840.64	768.93
Standard Deviation	15.53	41.66	202.31	114.08	98.50	53.59	87.61
National Income per Capita (Current Price): Mean	225.00	425.00	1,450.71	730.00	939.29	797.86	761.31
Standard Deviation	16.05	92.22	442.17	101.38	157.55	91.33	150.12

Table 1 results also show that the indicators of financial products and services usage include the number of deposit accounts and the number of loans and borrowers at commercial banks per 1,000 adults. Accordingly, the average number of deposit accounts at commercial banks per 1,000 adults was 372. The highest was 1,314 in Kenya, shadowed by Rwanda (351), Uganda (350), and Tanzania (126). The lowest was 27 in Burundi and 62 in the DRC, respectively. The value of the sub-indicator was low compared to the global average in 2021, and approximately 273,254 in Saudi Arabia. The average number of loan accounts in commercial banks per 1,000 adults was 64.09, ranging from 9.36 (DRC) to 241.00 (Kenya). Synonymous values were 57.10 (Tanzania), 39.50 (Uganda), 26.40 (Rwanda), and 11.20 (Burundi), which are very low compared to other countries. The same data show that the average number of loan accounts in commercial banks per 1,000 adults is around 30 globally. In 2022, the values were about 200 and 113 banks per 1,000 adults in high-income countries and Sub-Saharan Africa, respectively. The number of borrowers from commercial banks per 1,000 adults was also low, averaging 58 per 1,000 adults. Kenya had the highest average (217), and Burundi had the lowest average (8). The values for Tanzania were 44, Uganda (34), and Rwanda (30). In 2022, the average number of borrowers from commercial banks was 50 per 1,000 adults in Sub-Saharan Africa, 149 in middle-income countries, and 10 in lower-income countries[vi]. These three indicators demonstrate the impact and effectiveness of financial services on people's lives. Simply having access to financial services (like bank accounts) is not enough; active use truly signifies financial inclusion and its benefits.

In Table 1, the indicators of financial inclusion quality included the number of registered mobile money agent outlets per 100,000 adults and the number of mobile money transactions per 1,000 adults in a reference year. Quality indicators are crucial for financial inclusion, as they enhance the stability of the economic system and the effectiveness of financial inclusion policies. The average number of registered mobile money agent outlets was 879 per 100,000 adults. The numbers were relatively high in Tanzania (1,632), Kenya (1,300), and Rwanda (1,060) compared to DRC (375) and Burundi (26). The number of mobile money agents in East Africa exceeded the average for Sub-Saharan countries. According to the Energy Catalyst report (2024), the average density of active and registered mobile money agents in Sub-Saharan Africa is around 228 per 100,000 adults. The number of mobile money transactions per 1,000 adults per year averaged 32,655. It was very high in Uganda (64,695) and very low in Burundi (73) and the DRC (9,881), compared to Rwanda (41,971), Kenya (41,699), and Tanzania (37,609). The number of mobile money transactions in East Africa is relatively high compared to other countries in Sub-Saharan Africa. For example, mobile money transactions were 175,453 per 1,000 adults in South Africa, 314,623 in Ghana, and 105,476 in Nigeria in 2022, respectively.

The results in Table 1 indicate that when using the United Nations Sustainable Development Goals financial inclusion indicators only (i.e., the number of ATMs and commercial bank branches per 100,000 adults) across countries, the average estimated multidimensional financial inclusion index was in the medium category (0.426), ranging from very low categories in DRC (0.070) and Burundi (0.254) to high categories in Kenya (0.81) and Rwanda (0.562). Tanzania (0.438) and Uganda (0.402) were in the medium category. Including other indicators, as suggested by the G-20 member countries, lowers the average estimated financial inclusion index to 0.230 (in the lower category). The Global Microscope for Financial Inclusion Report by the Economist Intelligence Unit for 2024 utilizes UNDP indicators. It reports that the global average financial inclusion score was 0.634 in 2023, up from 0.625 in 2022. The report also shows that the average score on the global financial inclusion index in developed countries was 0.786, while in developing countries, it was 0.581. The Principal Financial Group report also for 2024 utilizes G-20 indicators to estimate the global financial inclusion index at 0.473 in 2023 and 0.417 in 2022, respectively. The analogous values for 2023 and 2022 are 0.312 and 0.266 in Africa, 0.423 and 0.403 in the Middle East, 0.467 and 0.442 in Europe, 0.483 and 0.417 in the Asia Pacific, and 0.504 and 0.468 in the Americas. The lower estimate for Africa is attributed to the limited fintech space and business confidence sub-indicators, as emphasized by the principal financial group methodology, which utilizes a diversified suite of financial products, including insurance, investment management, and retirement planning solutions, to estimate the index.

Table 1 also presents the summary statistics on GNI per capita, in both constant U.S. dollars (2015) and current prices. GNI per capita is directly related to economic growth, representing the average income of a country's residents. A higher GNI per capita indicates a higher level of economic activity and overall wealth within a nation, signifying a higher level of economic growth. Essentially, when a country experiences economic growth, its GNI per capita tends to increase (Roser, 2019). For the study period, the average was calculated, except for Kenya, which fell into the low-middle income category (with an average GNI per capita of $1,417). During the study period, all other countries in East Africa fell into the low-income category, with a GNI per capita of less than $1,000. Kenya crossed the threshold to become a low-middle-income country in 2014. The expectation is that it will become a middle-income country by 2030 (Ndung'u, Thugge, & Otieno, 2011). Moreover, the World Bank upgraded the Tanzanian economy from low to lower-middle income in 2020 (Turuka, 2022).

Rwanda envisions becoming a middle- and high-income country by 2035 and 2050 (GOR, 2016), and Uganda plans to reach upper-middle-income status by 2040 (Republic of Uganda, 2013). According to the current World Bank classification, many African countries are in the lower-income category. The primary cause of lower GNI per capita in African countries is a combination of factors, including low levels of productivity due to limited access to education, healthcare, and advanced technology, coupled with rapid population growth, which distributes the national income across a more significant number of people resulting in a lower per capita income compared to developed nations. Appendix 1 illustrates the distribution of financial inclusion and per capita national income in each country for the study period.

Table 2 shows the summary statistics of the independent variables by country. Life expectancy at birth measures the health dimension of the Human Development Index (Anand & Sen, 1994); it indicates the expected average number of years a newborn can expect to live if current mortality patterns persist. The life expectancy at birth was highest in Rwanda (65.06 years), and lowest in the DRC (58.46); the average for East African countries was 61.70 years. As of 2022, the life expectancy at birth in Sub-Saharan Africa was approximately 60.7 years, while in high-income countries, it was around 80 years. The top countries with the highest life expectancies in 2022 were Japan, Switzerland, and Australia, with life expectancies ranging from 83 to 84 years. In the same year, the life expectancy at birth in the United States was 74.8 years. Many factors, including health habits, diseases, genetics, and access to healthcare, can contribute to low life expectancy at birth (Chen et al., 2018).

The mean years of schooling (Table 2) represents the average number of years of education a population has completed. It is a standard method for measuring a country's human capital (Chen et al., 2023). The mean years of schooling in East African countries were 5.28 years, with the highest being 7.03 years in Kenya and 5.81 years in Uganda, and the lowest being 2.63 years in Burundi. The mean years of education in many Sub-Saharan Africa and South Asia regions are typically between 5 and 6 years, which is significantly lower compared to high-income countries with an average of 12 years. Although still low, the average number of years of schooling in East Africa has increased steadily over time. Also, the expected years of schooling for children in Table 2 are the years a child is likely to spend in school. The variable indicates the future level of education and, therefore, the country's human capital in the years to come (Gomez et al., 2024). The expected years of schooling for children were highest in Uganda (11.18 years), Kenya (11.1 years), and Rwanda (11.04 years), and lowest in Tanzania (8.56 years) and the DRC (9.22 years). The average years of schooling for children in Burundi was 10.52 years, and the average for all countries was 10.26 years. According to data from the Mo Ibrahim Foundation, in 2022, the expected years of schooling for children in Sub-Saharan Africa were around 8.5 years, with higher values observed in South Africa, Nigeria, and Lesotho, especially among females.

Table 2. Covariates Included in the Global Base Model

Variable	Burundi	DRC	Kenya	Rwanda	Tanzania	Uganda	Average
Life expectancy at birth in years: Mean	60.05	58.46	61.76	65.06	64.13	60.73	61.70
Standard Deviation	1.96	1.4	0.8	1.61	2.7	2.36	1.81
Mean years of schooling for adults: Mean	2.63	6.5	7.03	4.21	5.48	5.81	5.28
Standard Deviation	0.49	0.64	0.72	0.45	0.16	0.37	0.47
Expected years of schooling for children: Mean	10.52	9.22	11.01	11.04	8.56	11.18	10.26
Standard Deviation	0.47	0.37	0.29	0.21	0.5	0.26	0.35
Inflation (2010 base year): Mean percentage	161.01	166.01	157.22	128.14	157.07	154.19	153.94
Standard Deviation	45.4	72.51	41.77	21.88	37.41	32.63	41.93
Unemployment rate (%): Mean	1.35	4.56	3.71	12.2	2.65	3.22	4.62
Standard Deviation	0.26	0.39	1.28	1.41	0.41	0.55	0.72
Women (15-64 years) participation in labor force (%): Mean	80.70	63.90	71.90	56.40	81.20	67.50	70.27
Standard Deviation	0.85	1.25	0.36	1.13	2.86	0.86	1.22
Broad money (% of GDP): Mean	32.78	14.84	38.46	19.78	22.04	19.07	24.50
Standard Deviation	10.84	6.83	2.87	3.18	1.56	2.42	4.62
Internet use (% of population): Mean	3.87	9.52	18.71	15.92	13.28	5.79	11.18
Standard Deviation	3.74	9.48	10.63	8.73	10.23	1.54	7.39
Population density (number/km2): Mean	421.53	35.57	83.14	480.04	60.91	193.49	212.45
Standard Deviation	50.34	4.96	7.67	48.6	7.99	25.82	24.23
Aid and assistance (2021 10,000 US $): Mean	56,238	303,493	277,046	119,726	273,531	200,030	205,011
Standard Deviation	1,178	1,279	1,246	1,182	1,120	1,223	1,205
Net foreign direct investment (% of GDP): Mean	1.47	4.21	1.06	2.69	2.82	3.41	2.61
Standard Deviation	2.37	3.47	0.88	0.82	1.35	1.13	1.67
Cross capital formation (% of GDP): Mean	13.65	22.38	20.84	23.8	36.14	25.84	23.78
Standard Deviation	2.95	5.12	1.72	2.13	3.17	2.12	2.87
Agricultural value added (2015 US current billion $): Mean	0.97	6.92	13.55	2.10	13.09	8.02	7.44
Standard Deviation	0.05	0.90	1.47	0.40	2.28	1.07	1.03
Net trade in goods and services (current 10,000 US$): Mean	-66,552	-153,257	-756,881	-137,120	-267,442	-305,541	-281,132
Standard Deviation	17,496	90,650	192,216	29,746	169,993	102,059	100,360

In Table 2, the Consumer Price Index measures average inflation, using a 2010 base year. It tracks how quickly the prices of goods and services rose, and it was 153.94 percent for the East African Countries. The results indicate that the cost of goods and services increased by 53.94% since 2010. The highest increases were in DRC (66.01%) and Burundi (61.01%). The 2010 base year inflation data from the World Bank database covering 1987 countries, the average inflation for 2009/2022 was 194.79 percent with a skewness of 10.06, meaning that worldwide, prices rose by 94.79 percent from 2010 to 2022, on average, and inflation was highly skewed to the right. The five lowest values were 99.36, 100.16, 100.55, 101.77, and 102.10 percent, recorded in Switzerland, Nauru, Brunei Darussalam, Kiribati, and Comoros, respectively. The highest values were 377.78, 432.86, 566.49, 507.64, and 836.66 in Belarus, the Islamic Republic of Iran, the Bolivarian Republic of Venezuela, Sudan, and South Sudan, respectively. While the East African countries are below the World average, they are above the World median of 116.71 percent; therefore, they are among the countries with higher inflation.

The unemployment rate in Table 2 is a crucial economic indicator, as it provides a key insight into the health of a nation's economy by measuring the percentage of the labor force that is currently unemployed and actively seeking work; a low unemployment rate generally signifies a strong economy, while a high rate indicates a weak economy and potential economic issues. However, measuring unemployment in low-income countries is challenging (Liboreiro, 2023) due to the prevalence of informal employment, discouraged workers, and a lack of reliable labor market information. The average unemployment rate for 2009/22 in East African countries was 4.62 percent, ranging from 1.35 percent in Burundi to 12.20 percent in Rwanda. According to recent data, the unemployment rate in Sub-Saharan Africa is approximately 5.97 percent for 2023, representing a slight decline from the previous year. In contrast, the unemployment rate in high-income countries is around 4.5 percent. Rwanda and other developing countries experience a high unemployment rate primarily due to a mismatch between available jobs and the skills of the workforce (Feng, Lagakos & Rauch, 2024), limited job creation despite economic growth, a large youth population with inadequate training, and the prevalence of informal employment, leading to a skills gap and underemployment, especially among young people.

The female labor force participation rate is the ratio of women employed or actively seeking work to the total number of women within the working-age population, that is, those aged 15 and older. The measure of women's participation in the labor force, as shown in Table 2, is crucial for economic growth, social development, and gender equality. It contributes to higher GDP (Jabeen et al., 2020) by reducing poverty, improving living standards for families, and empowering women by providing them with financial independence. More significantly, when women actively participate in the workforce, it benefits both the economy and society (Anderson et al., 2021). The average female labor force participation rate (15-64 years) was high in Tanzania (81.20%) and Burundi (80.70%), and lower in the DRC (63.90%) and Uganda (67.50%), with an average of 70.27 percent in East African Countries. These values are relatively higher than the global average. According to data from the World Bank, the female labor force participation rate in Sub-Saharan Africa for women aged 15 and older is approximately 60.70 percent. The average in high-income countries is between 55% and 60%, and the global average has remained relatively stable at around 50%. Therefore, women in East Africa have a significant presence in the workforce. However, most of this participation is likely to be within the informal sector, particularly in agriculture. According to Klasen et al. (2022), Poverty drives a high female labor force participation rate in many developing countries. Women must work to contribute to household income, particularly in sectors such as agriculture, where subsistence activities are the primary means of survival and there are limited alternative income sources.

The estimate of broad money in Table 2 represents the proportion of an economy's total money supply (including cash, quickly convertible deposits, and other liquid assets) relative to the economy's overall size, as measured by GDP. The value indicates the proportion of money circulating within an economy compared to the total value of goods and services produced in that economy. A higher percentage suggests a potentially more significant level of liquidity in the economic system. Broad money is related to financial inclusion because it can impact the ability of central banks to manage monetary policy effectively. Sanderson, Mutandwa, & Le Roux (2018) show that when financial inclusion is low, a significant amount of money is outside the banking system, making it more challenging for central banks to manage the economy effectively. There is no accepted recommended rate for broad money as a percentage of GDP. The optimal level varies significantly depending on a country's economic context, but a typical range considered healthy is between 100% and 150%. For example, Broad money (as a percentage of GDP) in the United States was 99.13 percent in 2023, averaging 138 percent in high-income countries and 50 percent in low-income countries, respectively. At an average of 24.50 percent, the broad money supply in East African countries is relatively very low.

Internet use is crucial for financial inclusion, as it enables individuals, particularly those in underserved communities, to access various financial services, such as payments, savings, loans, and insurance, through digital platforms. Often, the costs are lower and more convenient than those of traditional banking methods, as Chaimaa, Najib & Rachid (2021) explain. Internet access empowers marginalized populations by promoting financial inclusion that fosters economic participation (Ye & Yang, 2020). The results in Table 2 indicate that the estimated average internet use in East Africa was 111.8 individuals (11.18%) per 1,000 adults. The highest internet use per 1,000 adults was in Rwanda (15.92%) and Kenya (18.71%), and the lowest in Burundi (3.87%) and Uganda (5.79%). The average internet use per 1,000 adults in high-income countries is approximately 930 people, indicating that roughly 93% of adults in these countries use the internet. The estimates for low-income and Sub-Saharan countries are 270 (27%) and around 250-300 users per 1,000 adults, implying that roughly 27% and 25-30% of adults in low-income and Sub-Saharan countries use the internet, respectively. The internet use rate in East Africa is significantly lower than that in other regions globally.

The 2024 Statista data show that Eastern Africa had the largest population in Africa, with 514 million people. The Southern Africa subregion has the smallest population, approximately 69 million people, followed by Middle Africa (220 million people), Northern Africa (276 million people), and Western Africa (465 million people). To calculate population density, divide the midyear population by the land area in square kilometers. For the East African countries in 2009/2022, the population density was 212.45 people per square kilometer (Table 2). The highest densities were in Rwanda (480.04 people/km^2), and Burundi (421.53 people/km^2), and the lowest densities were in the DRC (35.57 people/km^2), Tanzania (60.91 people/km^2), and Kenya (83.14 people/km^2). When considering high-income countries, Singapore stands out as having the highest population density (8,000 people/km^2), with a vast number of people living in a relatively small area, making it one of the most densely populated countries globally. Greenland has the lowest population density in the world, with a density of around 0.14 people per square kilometer. Population density plays a significant role in financial inclusion by influencing the accessibility and cost-effectiveness of delivering financial services. Oyewole et al. (2024) demonstrate that higher population densities generally correlate with greater financial inclusion, as economies of scale allow serving a more extensive customer base within a smaller geographical area.

Wafiq & Suryanto (2021) argue that population density plays a significant role in economic growth, with a high density often contributing to positive factors like increased market size, readily available labor, knowledge sharing, and infrastructure development. Hussain et al. (2022) argue that a high population density may also lead to adverse economic effects, such as increased congestion, resource overuse, and heightened competition, if not managed effectively. Optimal population density is a density that balances the needs of a society with the environmental carrying capacity, allowing for economic growth while minimizing resource depletion, depending on geography and technology. Worldwide, Salem (2023) cites a sustainable population density of around 50-100 people per square kilometer for most regions.

Table 2 also summarizes aid and assistance variables (i.e., official development assistance (ODA)) that can positively influence economic growth by providing capital for investment in critical infrastructure, education, and healthcare. As Nwokolo et al. (2023) show, investment increases productivity, human capital development, and financial stability. However, according to Kaliba et al. (2008) and Bourhrous, Fazil & O'Driscoll (2022), aid effectiveness heavily depends on factors such as good governance, policy alignment, and the recipient country's capacity to absorb aid effectively. Concerns persist regarding the potential distortions of local markets if the management of assistance is inadequate.

For 2009/2022, the East African countries received an average of $2.05 billion annually. The DRC received the highest aid and assistance ($3.04 billion/year), followed by Kenya ($2.77 billion/year) and Tanzania ($2.74 billion/year). Burundi received the lowest aid and assistance ($0.56 billion/year), followed by Rwanda ($1.2 billion/year). The average ODA for Sub-Saharan Africa is around $32 billion annually, representing a significant portion of total global aid. In Sub-Saharan Africa, Ethiopia received the highest net official development assistance from official donors in 2022, amounting to approximately $5 billion. Nigeria was the second largest recipient ($4.54 billion/year). Worldwide, the World Bank data show that in 2022, the total aid amounted to about $211 billion in 2020 prices; Ukraine received the highest net sum ($29.29 billion), followed by Syria ($8.20 billion) and Egypt ($6.08 billion). Comparatively, DRC ($3.33 billion), Kenya ($2.733 billion), and Tanzania ($2.728 billion) were among the 20 countries that received the highest net sum of ODA from official donors in 2022.

Net foreign investment in Table 2 refers to the difference between the amount of investment made by a country's residents in foreign countries and the amount of investment made by foreign residents within that country. It represents the net flow of capital from a country to the rest of the world, calculated by subtracting the inward foreign investment from the outward domestic investment. Its impact can significantly influence a nation's economic growth (Alfaro & Chauvin, 2020) by stabilizing local currency stability and overall financial health, by affecting job creation, technology transfer, and access to capital. Foreign Direct Investment (FDI) can also positively impact financial inclusion by increasing access to financial services for a broader population (Odugbesan et al., 2022), by bringing new financial technologies, expanding the financial sector, and providing capital to local businesses. These services enable more people to participate in the formal financial system. In East Africa, the rate of FDI relative to GDP for the study period ranged from 1.06 percent in Kenya to 4.21 percent in the DRC, averaging 2.61 percent. The value was lower in Burundi (1.47%), Tanzania (2,82%), and Rwanda (2.69%), and relatively higher in Uganda (3.41%). While figures may vary slightly depending on the source, the average FDI as a percentage of GDP in Sub-Saharan Africa is generally around 1.8 percent of GDP and around 3-5 percent in developing countries. In 2023, countries with high foreign direct investment as a percentage of GDP included Guyana (42.88%), Singapore (34.95%), and Hong Kong (29.08%).

Also known as gross domestic investment, gross capital formation (GCF) refers to the total amount spent on adding to a country's fixed assets and inventories (Table 2). The GCF positively impacts economic growth, as it represents investment in new capital goods, such as machinery and infrastructure, which directly contribute to increased production capacity and ultimately lead to higher GDP levels in an economy. Topcu, Altinoz & Aslan (2020) argue that a higher GCF signifies more potential for future economic expansion. For the period under study, the average gross capital formation as a percentage of the country's GDP was 23.78 percent. The rates were 32.14 percent in Tanzania, 25.84 percent in Uganda, and 23.8 percent in Rwanda. Other values were 22.38 percent (DRC), 20.84 percent (Kenya), and 13.65 percent (Burundi). The average gross capital formation as a percentage of GDP in Sub-Saharan Africa is approximately 20 percent, and it falls within a range of 20 to 25 percent in high-income countries. Except for Burundi, the GCF in East Africa is comparable to the global values.

In Table 2, the agricultural value added refers to the increase in the economic value of a raw agricultural product through processing, packaging, or other methods that transform it into a more desirable product for consumers, allowing producers or farmers to command a higher price in the market. Agricultural value-added activities enable farmers (the majority of the population) to capture a higher income by creating products with a higher perceived value. In these countries, adding value to agricultural products is crucial for economic growth as it stimulates revenue generation for rural communities, creates new jobs, and expands the government's tax base. In East African countries, the agricultural value added averaged U.S. $7.44 billion annually from 2009 to 2022, with Kenya ($13.55 billion) and Tanzania ($13.09 billion) recording the highest average value, and Uganda ($8.02 billion) and the DRC ($6.92 billion) recording intermediate values. The lowest was in Rwanda (U.S. $2.10 billion) and Burundi (U.S. $0.97 billion), reflecting their small economies. According to data from the World Bank, the average agricultural value added in Sub-Saharan Africa in 2022 was approximately 17.3% of the region's GDP; however, in some countries, such as Ethiopia and Chad, the contribution reached up to 40% and was estimated at $230 billion in 2025 U.S. constant dollars. The same year, South Africa ($97.2 million) was followed closely by Nigeria ($25.5 billion). The values represented approximately 2.7% and 23.69% of the total value added to the economy, respectively.

The last part of Table 2 represents the net trade in goods and services, which is the difference between a country's exports and imports of goods and services. Net trade significantly impacts a nation's economy by influencing its GNI, employment levels, currency value, and overall economic growth. A positive net trade

(trade surplus) contributes to economic expansion. In contrast, a negative net trade (trade deficit) can put downward pressure on the economy by reducing aggregate demand and potentially leading to job losses in export-oriented sectors. During the study period, all countries experienced a trade deficit, with Kenya ($-7.57 billion) leading the way, followed by Uganda ($-3.06 billion), Tanzania ($-2.67 billion), and the DRC ($-1.53 billion). The trade deficits in Rwanda and Burundi were $-1.37 billion and $ 0.67 billion, respectively, with the average for all countries being $2.81 billion. The countries with the most significant trade deficits in 2022 included the U.S., Mexico, Vietnam, and Ireland. For example, in 2022, while the U.S. had the most significant trade deficit in the world ($822 billion), China had a substantial trade surplus of $317 billion. A trade deficit, where a country imports more goods and services than it exports, can indirectly impact financial inclusion, primarily through its effects on economic growth and the availability of financial services. Although the relationship is not direct, the trade deficit can affect factors that influence financial inclusion, including access to credit, income levels, and the development of economic infrastructure.

4.2 Results of the Multivariate Model

4.2.1 Variable selection and testing for the model fit

Based on Figure 2, we estimated two categories of models for both full and reduced models as explained above. Both models utilized the noncentered spline as explained by Tikka & Helske (2023). The splines determine how variables change over time, capturing nonlinear patterns in the data and thereby enhancing the model's convergence and stability. For each channel (i.e., 2.1 and 2.2), we applied the Least Absolute Shrinkage and Selection Operator (LASSO) of Tibshirani (1996) and Kukreja, Löfberg & Brenner (2006) to select a smaller set of predictors from the global base model, resulting in a manageable reduced model. The LASSO method performs both variable selection (i.e., identifying and discarding irrelevant predictors listed in Table 2) and regularization, which prevents overfitting. The results in Table 3 are from the Dynamite R package (Tikka & Helske, 2023). As stated above, the package applies the Bayesian framework by using a Markov Chain Monte Carlo (MCMC) algorithm via the Stan programming language (Carpenter et al., 2017), making it necessary to check the model diagnostics before interpreting model results. The results in Table 3 display diagnostic indicators for both the global and reduced models. The diagnostic statistical tools in Table 3 are potential scale reduction statistics (Rhat), the effective sample size (bulk-ESS) based on rank-normalized draws, and the tail effective sample size estimate (tail-ESS). As explained above, the UNDP-MFII is a model that provides basic financial inclusion services, measured by two indicators. In contrast, the G-20 MFII offers more comprehensive financial inclusion services by including additional indicators.

Table 3. Diagnostic Results for the Global and Reduced Models

Model Category	MFII Model	Response	Smallest BulK-ESS	Smallest Tail_ESS	Largest Rhat
Reduced model: category 1	UNDP		4559	1760	1.0006
	G20		3199	1204	1.0005
Reduced model: category 2	UNDP		12115	11020	1.0009
	G20		3938	1778	1.0002
Global model: category 1	UNDP		502	311	3.2987
	G20		542	412	3.6295
Global model: category 2	UNDP		562	431	3.1639
	G20		872	611	3.7372

Note: UNDP denotes the United Nations Development Program, and G20 is the Group of Twenty.

Vehtari et al. (2017) recommend ensuring Rhat values are below 1.01. Berger, Bayarri, & Pericchi (2014) explain that the bulk-ESS provides insight into the autocorrelation among samples in the same chain. Also, Vehtari et al. (2017) clarify that the tail-ESS diagnoses the sampling efficiency of the tails of the posterior, which is the minimum of the effective sample sizes for the 5th and 95th percentile quantiles. Carpenter et al. (2017) recommend that the values of bulk-ESS be more than 100 times the number of chains in the model; in this case, 3. Also, the values of tail-ESS should be sufficiently large. If the tail-ESS is too low, it indicates that the posterior variances and tail quantiles may be unreliable. In Table 3, all R-hat values are close to 1, and the bulk-ESS and tail-ESS are sufficiently large for the reduced model, indicating that the results are statistically valid for prediction purposes.

4.2.2 The effect of financial inclusion on gross national income

In the reduced models, the time-invariant variables that influenced the multidimensional financial inclusion index (MFII) were life expectancy at birth in years, mean years of schooling for adults, expected years of education for children, annual inflation rate, unemployment rate, female labor force participation rate, broad money supply, number of internet users, and population density. The final variables influencing per capita gross national income (GNI) for reduced models were annual inflation and unemployment rate. Table 4 presents the results of the Pareto k statistics as explained above. The statistics are for selecting between model categories when estimating the short and long-term influences of financial inclusion on gross national income. Their associated plots are in Appendix 2.

Comparing the performance of the models with UNDP financial inclusion indicators, the category 2 model is better. The two models yield similar results for the k-value distribution, specifically 98.70 percent of "good" Pareto *k* diagnostic values. There is one outlier with a "very bad" Pareto *k* diagnostic value. The outlier is related to Kenya's 2013 gross national income ($ 1,252.02), which was significantly higher compared to other East African countries. Also, note the high value of the minimum ESS in the Category 2 model, 1,115, compared to 255 in the Category 1 model. The results suggest that the MCMC chains effectively explored the posterior distribution, and the samples are reliable for inference and model prediction for Category 2 with UNDP financial inclusion indicators. For the models with G-20 financial inclusion indicators, category 2 performs better than category 1. Category 1 has three outliers, also related to Kenya's high gross national income in 2013 ($1,252.02), 2017 ($1,511.94), and 2018 ($1,571.52). Category 2 has two outliers, also related to Kenya's high gross national income in 2013 ($1,252.02) and Tanzania's high female labor participation rate (85.34%) in 2010. For prediction purposes, these datapoints with outliers, which are real, were included in the final model. Increasing the number of iterations and warm-up samples during the model fitting process augmented the model reliability and prediction efficiency.

Table 4. Pareto *k* diagnostic values for category 1 and 2 Models

Type of Model	Pareto k statistics	Ranking	Frequency	Percent Frequency	Min. ESS
Category 1					
UNDP MFII	[-Inf, 0.7]	good	77	98.70%	255
	[0.7, 1]	bad	0	0.00%	NA
	[1, Inf]	very bad	1	1.30%	NA
G-20 MFII	[-Inf, 0.7]	good	75	96.20%	584
	[0.7, 1]	bad	2	2.60%	NA
	[1, Inf]	very bad	1	1.30%	NA
Category 2					
UNDP MFII	[-Inf, 0.7]	good	77	98.70%	1115
	[0.7, 1]	bad	0	0.00%	NA
	[1, Inf]	very bad	1	1.30%	NA
G-20 MFII	[-Inf, 0.7]	good	76	97.40%	813
	[0.7, 1]	bad	1	2.60%	NA
	[1, Inf]	very bad	1	1.30%	NA

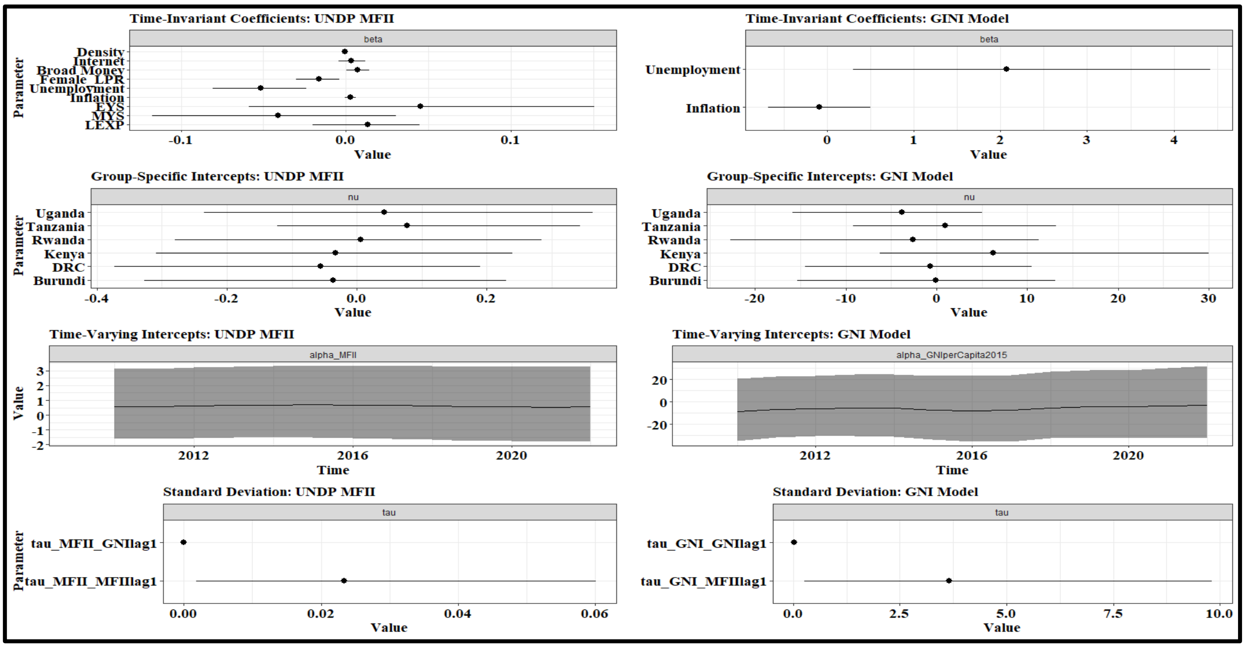
Note: UNDP denotes United Nations Development Program, G-20 Group of Twenty, and MFII multidimensional financial inclusion.

The estimated posterior distributions of parameters from Category 2 models, using UNDP and G-20 financial inclusion indicators, are presented in Appendix 3. The naming convention for the estimated parameters starts with the parameter type, followed by an underscore, and then the name of the response variable. In the case of time-invariant, time-varying, or random effects, it includes the name of the predictor variable, see Tikka & Helske (2023) and Helske & Tikka (2024) for additional details. For example, the time-invariant coefficients *beta_y_x* in Appendix 3 represent the effect of a predictor variable (*x*) on a response variable y, which remains constant over time. For clarity, Figure 2 presents the plots of the key parameters for both models. In Figure 2, the left panel shows results from channel 1 (expression 2.1) and the right panel presents the results from the second channel (expression 2.2).

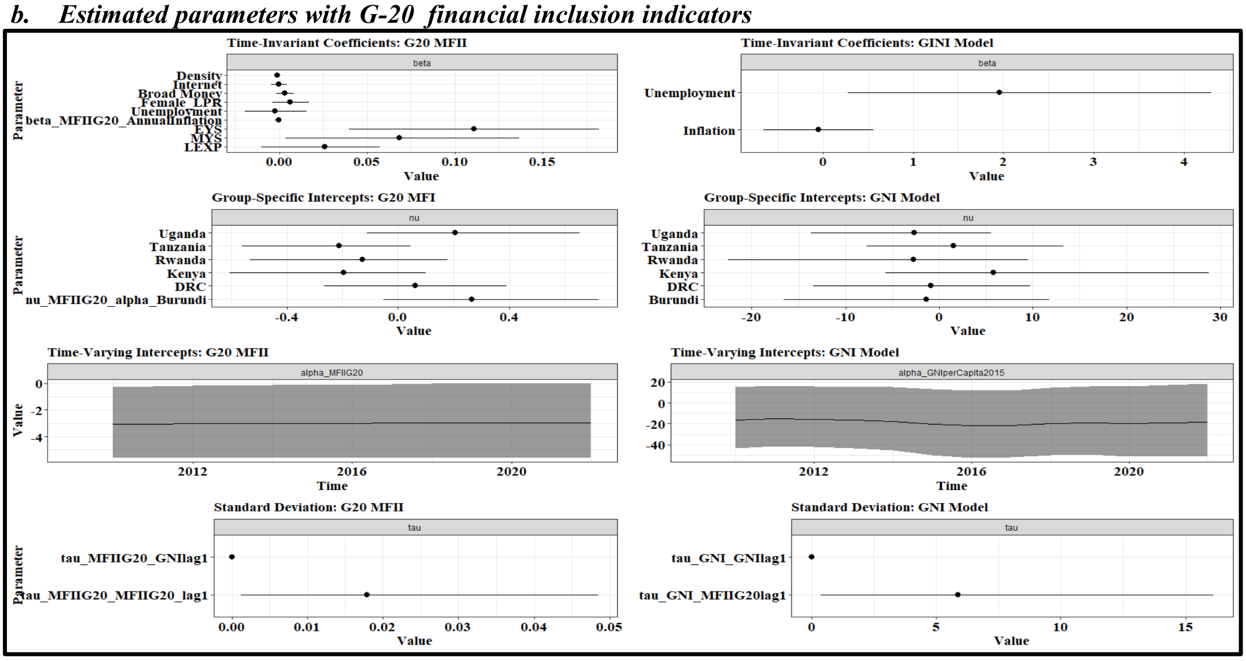
For both UNDP and G-20 models in Figure 2, the estimated time-invariant parameters indicate that population density (density) and inflation have a non-significant impact on the financial inclusion index. While some studies have found weak or insignificant correlations between these factors and financial inclusion, others have found significant relationships, particularly when considering specific contexts and dimensions of financial inclusion. Some studies, including Bashiru et al. (2023), suggest that population density may not be the primary driver of financial inclusion, particularly when considering factors such as access to financial services and other socioeconomic factors. Other research suggests that population density can be positively associated with financial inclusion, particularly in the context of agglomeration economies, where economic activities cluster, resulting in increased demand for financial services, as shown by Kumar (2013) in India. Inflation can negatively impact financial inclusion by eroding the purchasing power of individuals and discouraging savings and investment. As Gebrehiwot & Makina (2019) explain, the methodological differences may also influence the conclusions of these various studies.

Figure 2. Visuals of Various Aspects of the Fitted Models

a. Estimated parameters with UNDP financial inclusion indicators



b. Estimated parameters with G-20 financial inclusion indicators



In Figure 2, the time-invariant variables with intermediate but positive values for the UNDP model were the number of internet users and the broad money supply. Generally, increased internet user penetration and a larger broad money supply positively impact financial inclusion by enhancing access to financial services, promoting digital payments, and lowering transaction costs. Digital platforms, enabled by internet access, facilitate financial transactions, encourage savings and deposits, and make financial services more accessible and affordable. A larger money supply facilitates digital financial services by providing more resources to participants in the financial system. The Results in Figure 2 show that, on average, the expected years of schooling for children (EYS) and life expectancy at birth in years (LEXP) had a significant positive impact on the UNDP financial inclusion index. The female labor force participation rate, unemployment rate, and mean years of schooling for adults (MYS) had a significant negative impact on the UNDP financial inclusion index. The expected years of schooling for children mean years of education for adults, and life expectancy at birth in years had a significant and positive effect on G-20 financial inclusion. Notice that some estimated parameters varied significantly, as indicated by the wide confidence interval at the 5 percent level of significance. A wide interval means that the actual value of the coefficient could lie within a substantial range. For this study, the results are due to significant variability in the

East African data points, which increases uncertainty.

The expected years of schooling for children and life expectancy at birth in years are related to better financial literacy and improved decision-making skills, all of which are crucial for effective participation in the financial system (see, for example, Klapper & Lusardi, 2020). In the existing financial inclusion literature, high female labor force participation has a positive effect on financial inclusion, as discussed above. Female labor force participation can sometimes present challenges to financial inclusion, often due to factors such as income inequality within households and the types of jobs women hold. Ke (2021) and Morsy (2020) note that social norms may hinder their access to and control over finances. Higher unemployment rates negatively impact financial inclusion by limiting access to income, assets, and opportunities to build credit and savings, which are essential for financial independence and participation in the formal financial system. As presented by Sikka & Bhayana (2024), reduced income and economic activity, coupled with societal norms and stereotypes, can create barriers to accessing financial services, further exacerbating financial exclusion.

The GNI model in Figure 2 included the unemployment rate and inflation as time-invariant variables for both the UNDP and G-20 models. While inflation has a negative effect on GNI for both models, the unemployment rate has a positive effect. As explained above, Inflation negatively impacts GNI primarily by eroding purchasing power, distorting investment decisions, and creating economic uncertainty. When prices rise faster than wages and incomes, people can afford fewer goods and services, leading to a reduction in overall demand and economic activity. It leads to decreased production and a lowering of GNI. As explained by Okun's law, a rise in the unemployment rate would have a negative impact on GNI as it corresponds to a decrease in a country's output. Since

GNI is closely related to GDP; a decline in GDP due to increased unemployment is likely to result in a corresponding reduction in GNI. The results in Figure 2, however, indicate that the rise in the unemployment rate has a positive impact on GNI. According to Stephens (2002) and Lee & Parasnis (2014), in developing countries, the added worker effect can lead to an increase in the labor force, which in turn increases GNI, even as unemployment rises. This effect occurs when family members, often women, enter the workforce to compensate for the loss of income when another family member becomes unemployed. Studies have found that this effect is more pronounced in developing nations due to factors like lower average incomes, limited social safety nets, and a greater reliance on family income.

For both the MFII and GNI models, country-level intercepts vary by country; some are negative, with wide confidence intervals that reflect the uncertainty in estimating each one. The wide interval indicates how each country deviates from the population averages, as the base of these intervals is on the data available within each country and the overall distribution of intercepts. The results reveal a significant spread in the data points within and across East African countries, contributing to higher uncertainty in estimating each country's intercept and resulting in a wider confidence interval. In a Bayesian framework, as explained by Tikka & Helske (2023), the confidence interval is derived from the posterior distribution of the group's intercept, taking into account both the data and the prior distributions used in the model. As Ogle & Barber (2020) demonstrate, while negative random effects, or negative variance estimates, cannot be truly negative, computationally, negative estimates can arise due to country-level weak effects, or some models might yield negative results to achieve unbiased estimates of other parameters.

The time-varying and random effects parameters in Figure 2 are relatively constant and above zero for UNDP MFII and significantly below zero for the model with G-20 MFII and both GNI models. The predictors included in the time-varying formulation included the first-order lag of the financial inclusion index and per capita national income variables. A positive or negative coefficient means that as the predictor variable increases, the response variable also increases or decreases, assuming all other variables are held constant. If the coefficient is positive and growing over time, it suggests that the positive influence of the predictor on the response is becoming stronger. Conversely, if it is positive but decreasing, the positive impact is weakening, although it remains present. As shown in Figure 2, the time-varying parameters remained constant, implying that the model's properties and behavior were stable during the study period. By comparing changes in intercepts over time, the lagged values of MFII and GNI have had a similar effect across countries and over time. It is also important to note that indices with fewer indicators (such as the UNDP MFII) may not capture the full complexity of the measured phenomenon, leading to a narrower scope and potentially different results compared to an index with a broader range of indicators (such as the G-20 MFII).

The last part of the left panel in Figure 2 displays the parameter estimates for the lagged values of both MFII and GNI, representing the expected change in the current value of the response variable for a one-unit increase in the lagged predictor, holding all other predictors constant. A positive coefficient indicates that higher values of the lagged variable of MFII in the previous time step are associated with higher values of the current MFII. The magnitude of the coefficient indicates the strength of this relationship. While the lagged value of GNI did not have a significant impact on the current value of MFII for either model, the lagged values of MFII had a positive and significant impact, with a wide confidence interval at the 5 percent level of significance. Likewise, the lagged value of GNI did not have a considerable effect on the current value of GNI for either model; the lagged values of MFII had a positive and significant impact on GNI. The applied DMPM focuses on assessing the predictive ability of the model, rather than direct causation as explained by Helske & Tikka (2024). Even if past values of GNI correlate with current GNI, they may not necessarily accurately predict future values of MFII or GNI. A significant observation is that past values of MFII can predict future values of MFII or GNI. By utilizing past financial inclusion data to forecast future trends, it is possible to gain a deeper understanding of the factors driving financial inclusion and gross national income. The results help inform evidence-based policy making, enabling the development of more effective interventions, fostering financial stability, and promoting inclusive economic growth and social development.

5. Summary and Conclusion

Since the 1990s, research findings have consistently demonstrated a strong correlation between financial inclusion and increased economic growth and development. Studies show that financial inclusion has a positive impact on economic growth, particularly in emerging economies. For example, research in Bangladesh, Malaysia, and Pakistan found a significant positive impact on economic growth. Access to services like savings accounts has also helped mitigate economic shocks in low-income countries. Therefore, financial inclusion policies aim to provide accessible and affordable financial services, such as savings, credit, and insurance, to all, including underserved populations, and play a vital role in fostering economic growth and development. It is a crucial driver of economic growth and development, especially in developing countries, by expanding access to financial services, empowering marginalized groups, and fostering entrepreneurship and innovation.

The study examines the substantial impact of financial inclusion on gross national income in East African countries, underscoring its importance as a global policy priority. The study utilizes the Multidimensional Index of Financial Inclusion, a comprehensive measure that assesses the extent of financial inclusion within a country by considering various dimensions of access, usage, and barriers to financial services. It extends beyond simple measures, such as account ownership, to capture a more nuanced understanding of how well individuals and businesses integrate into the formal financial system. The measures of economic growth and development are the per capita gross national income. The East African Community includes Burundi, the Democratic Republic of Congo, Kenya, Rwanda, Somalia, South Sudan, Tanzania, and Uganda. Due to substantial missing data, the analysis excluded Somalia and South Sudan.

The data are analyzed using the dynamite package of Tikka & Helske (2023) within the R software environment, developed by the R Core Team (2023). The package implements a multivariate dynamic panel data modeling that offers several advantages, including the ability to analyze how multiple time-dependent variables simultaneously influence each other, control for individual-specific effects, and account for lagged effects of variables on themselves or other variables in the model. This approach facilitates a deeper understanding of the complex relationship between financial inclusion and gross national income within a panel data framework. It also enhances the efficiency and accuracy of statistical analysis.

The main results demonstrate that indicators of the Human Development Index (HDI), including years of schooling for children, life expectancy at birth, and mean years of schooling for adults, were key drivers of financial inclusion growth. Improved HDI indicators enable greater access to and usage of financial services. Policy-wise, strong HDI performance can foster financial inclusion by creating a more conducive environment for individuals to engage with formal financial services. Conversely, financial inclusion can further enhance human development by providing access to resources and opportunities that improve health and overall well-being.

The country-specific intercepts account for baseline differences between countries and show heterogeneity within them. East African countries often exhibit inherent differences in micro and macroeconomic policies that impact the dependent and independent variables, even when other predictors are held constant. While the DRC and Burundi performed poorly in providing basic financial services (according to the UNDP-MFII), countries such as Tanzania, Rwanda, and Kenya, which have significantly lower intercepts on the G_20 MFII, need to focus on improving overall financial inclusion. Additionally, the current study suggests a positive relationship between financial inclusion and per capita national income, implying that increased access to and usage of financial services in previous periods positively influence a nation's current and future GNI.

Because it takes time for financial inclusion to manifest its benefits, East African countries can boost entrepreneurship and business growth by increasing access to credit, capital, and savings, enabling businesses, especially small and medium-sized enterprises (SMEs), to expand, innovate, and create jobs, thereby contributing to GNI. Moreover, financial inclusion enables individuals to save, invest in education or healthcare, manage risks (e.g., through insurance), and participate in profitable economic activities, ultimately increasing household income and contributing to the country's gross national income. In particular, the study finds that financial inclusion policies implemented today have a significant positive impact on gross national income several years later, highlighting the importance of sustained efforts and long-term commitment to such initiatives. Country-level studies, by nature, are ecological studies and cannot be used to conclude about individuals within those countries.

Future research should focus on regions within countries or household-level studies that provide insights into the role of financial inclusion in improving individuals' economic well-being.

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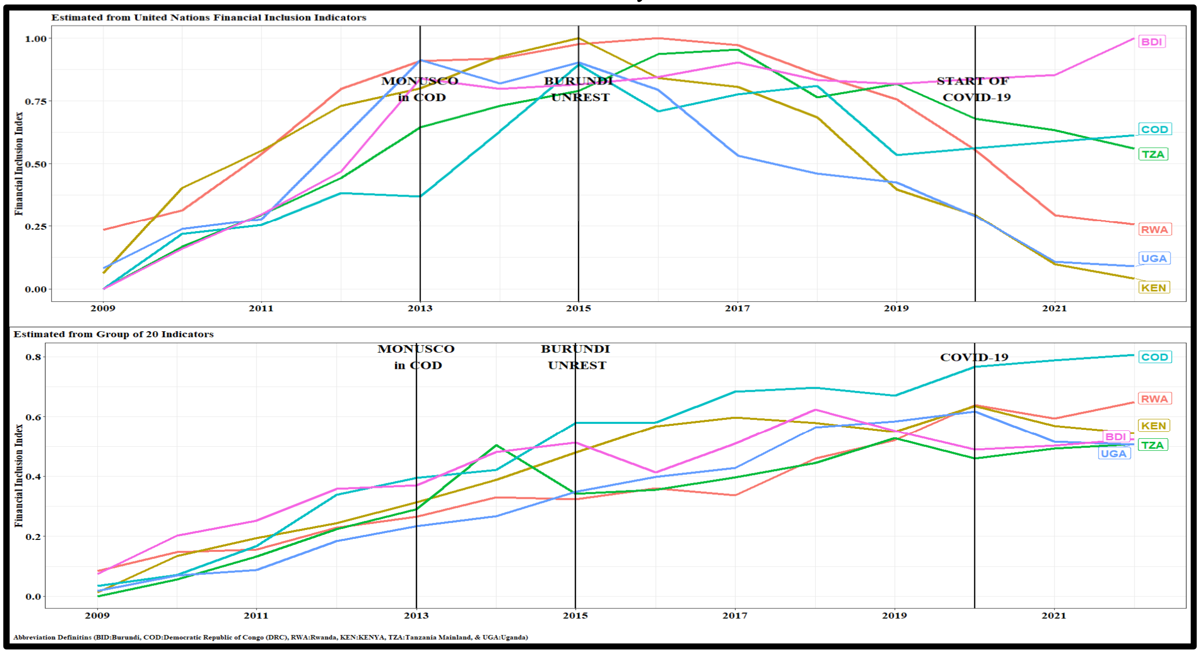
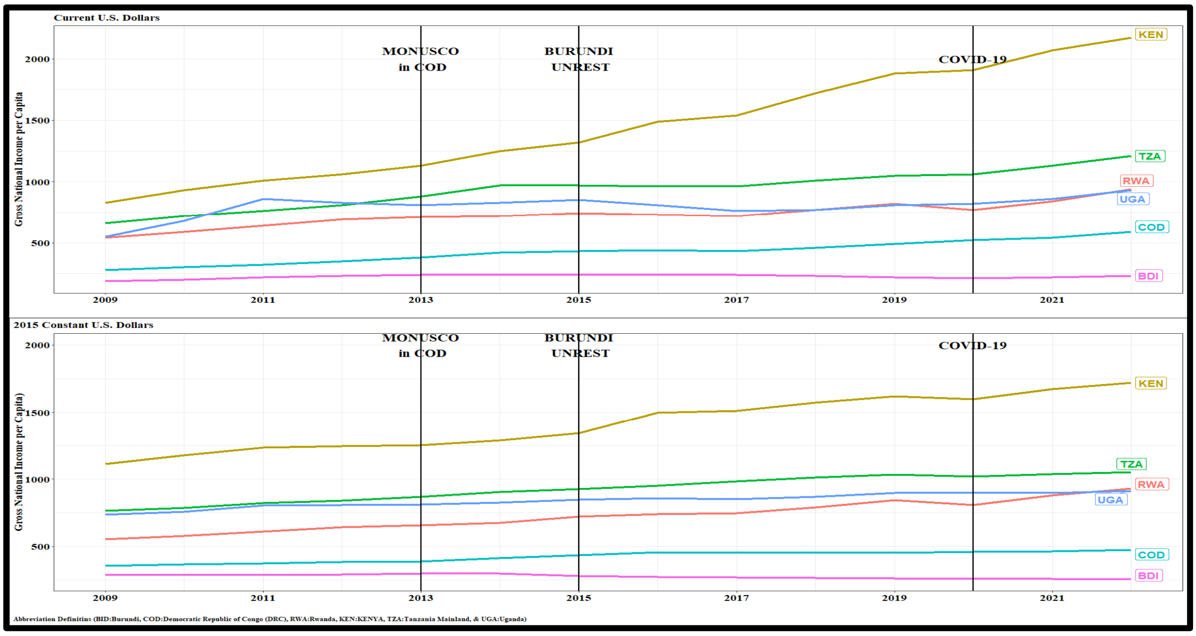
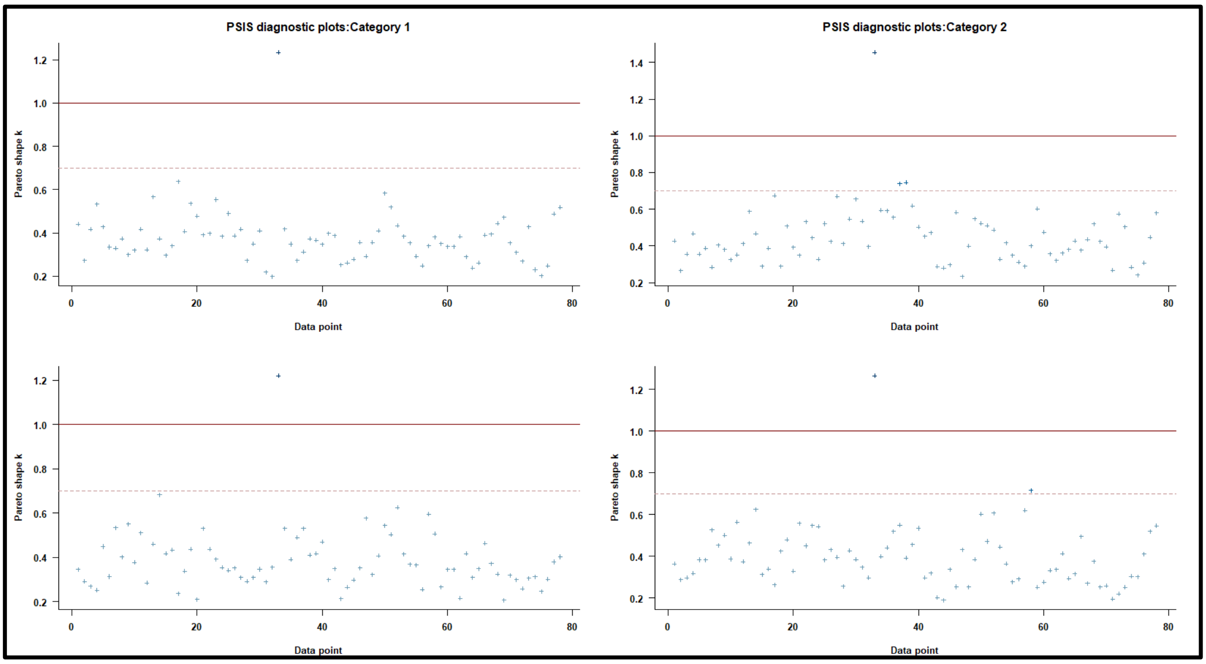
Appendix 1. Trend in the Multidimensional Financial Inclusion Index and Per Capita National Income by Country





Appendix 2. Pareto k diagnostic Plots



Appendix 3. Parameter Estimates from the Relationship between National Income and Financial Inclusion Using a Dynamic Multivariate Panel Model

In Appendix 3, let *y* be a response variable (i.e., either MFII or GNI), *x* be a predictor variable explained above, and t be a time dimension. The parameter *alpha_y_t* captures time-specific (*t*) variations in the response variable y (i.e., GNI or MFII) not explained by other predictors. Additionally, in Appendix 3, the time-invariant coefficients (*beta_y_x*) represent the effect of a predictor variable (*x*) on a response variable y, which remains constant over time. The *corr_nu_y1_alpha__y2_*alpha represents the correlation between the time-varying effects (alpha coefficients) of response variable *y1* (MFI) and response variable *y2* (GNI), across different countries. This parameter tells how the dynamics of MFII are related to the dynamics of GNI. A positive value would imply that when the time-varying effect of MFI increases, the time-varying impact of GNI also tends to increase. A negative value suggests that when the time-varying impact of MFI increases, the time-varying effect of GNI tends to decrease. A value close to zero would indicate little or no linear correlation between the time-varying effects of the two response variables.

The parameter annotated by *delta_y_ylag1* refers to the time-varying coefficient associated with the first-order lagged value of the response variable *y*. It represents how the lagged value of the response variable (ylag) influences the current value of the response variable (y). The value at a given time point would indicate the strength and direction of this influence (positive or negative). If it is positive and increasing over time, it suggests that the positive impact of past y values on current values is strengthening as time progresses. Also in Appendix 3, the *nu* parameter represents country-specific intercepts (random effects). The *sigma_nu* parameter would represent the standard deviation of the group-level random effects. A larger *sigma_nu* indicates greater variability in the random effect parameters across countries, meaning there are more substantial differences in the baseline levels or slopes of the outcome variable across those countries. Conversely, a smaller *sigma_nu* implies more similar group effects. Since the value of *alpha* measures a specific effect that changes over time within the model, *sigma_nu_y_alpha* quantifies the variability allowed in the way the time-varying effects (*alpha*) change over time for the specified response variable (y) within the model by incorporating group-specific variations as well. A smaller *sigma_nu_y_alpha* implies smoother changes in the time-varying effects, while a larger value allows for more rapid and potentially erratic adjustments. The last part of the table in Appendix 3, with *tau_y_ylag*, represents the component of the model's structure related to the variability or magnitude of the influence of past observations of *y* on its current value. The *tau_alpha_y* parameter is the standard deviation of the random effects for the intercept term within a specific response variable. A smaller value of *tau_alpha_y* suggests that the random effects for the intercept of *y* are relatively close to the overall average effect. A larger value indicates greater variability in the random effects, meaning that different countries in East Africa have significantly different baseline values for either MFII or GNI.

a: *Results from the model with UNDP financial inclusion indicators*

Estimated Parameter	mean	sd	LCI	UCI	bulk_ESS	tail_ESS
beta_ GNI_AnnualInflation	-0.093	0.360	-0.682	0.500	48559	23535
beta_ GNI_UnEmploymentRate	2.074	1.387	0.300	4.421	17129	10627
beta_MFII_AnnualInflation	0.003	0.002	-0.001	0.006	51450	38577
beta_MFII_EYS	0.045	0.064	-0.059	0.151	27943	32980
beta_MFII_FemaleLFP15_64	-0.016	0.008	-0.030	-0.004	21413	25266
beta_MFII_LEXP	0.013	0.020	-0.020	0.045	19603	27694
beta_MFII_MYS	-0.041	0.045	-0.118	0.030	23697	26631
beta_MFII_NumInternetUsers	0.003	0.005	-0.005	0.012	22069	30704
beta_MFII_PopDensity	-0.001	0.001	-0.002	0.000	16798	22719
beta_MFII_UnEmploymentRate	-0.052	0.017	-0.081	-0.024	25352	30804
beta_MFII_Broadmoney	0.007	0.004	0.000	0.014	19793	27259
alpha_GNI[2010]	-8.940	19.276	-35.149	21.047	21874	11767
alpha_GNI[2011]	-7.066	18.728	-31.765	22.403	21798	11741
alpha_GNI[2012]	-2.215	18.743	-30.860	23.158	21685	12067
alpha_GNI[2013]	-5.772	18.982	-30.678	24.343	21280	11976
alpha_GNI[2014]	-5.701	19.237	-31.225	24.610	21814	12232
alpha_GNI[2015]	-7.231	19.548	-33.616	23.437	22650	12336
alpha_GNI[2016]	-8.154	19.988	-35.761	23.189	22646	12885
alpha_GNI[2017]	-7.655	20.124	-35.501	24.107	22795	13074
alpha_GNI[2018]	-5.500	20.077	-32.765	26.808	23148	13156
alpha_GNI[2019]	-4.212	20.143	-31.542	28.595	23162	13469
alpha_GNI[2020]	-4.505	20.220	-32.205	28.433	23134	13582
alpha_GNI[2021]	-3.508	20.498	-31.556	30.118	23873	13619
alpha_GNI[2022]	-2.987	21.072	-32.182	32.315	23602	14214
alpha_MFII[2010]	0.571	1.456	-1.597	3.110	18338	23948
alpha_MFII[2011]	0.584	1.463	-1.595	3.144	18306	23665
alpha_MFII[2012]	0.645	1.472	-1.536	3.228	18275	23297
alpha_MFII[2013]	0.682	1.483	-1.510	3.290	18244	23298
alpha_MFII[2014]	0.679	1.495	-1.528	3.306	18161	23273
alpha_MFII[2015]	0.698	1.506	-1.519	3.344	18129	23273
alpha_MFII[2016]	0.664	1.518	-1.581	3.330	18054	23208
alpha_MFII[2017]	0.651	1.529	-1.616	3.334	18000	23216
alpha_MFII[2018]	0.619	1.539	-1.673	3.312	17957	23461
alpha_MFII[2019]	0.589	1.548	-1.726	3.294	17895	23394
alpha_MFII[2020]	0.570	1.554	-1.759	3.278	17875	23571
alpha_MFII[2021]	0.550	1.558	-1.795	3.256	17871	23488
alpha_MFII[2022]	0.554	1.567	-1.807	3.273	17815	23691
corr_nu_MFII_alpha__ GNI_alpha	-0.119	0.571	-0.934	0.843	23203	30019
delta_ GNI_ GNI_lag1[2010]	1.044	0.030	0.999	1.081	16179	8721
delta_ GNI_ GNI_lag1[2011]	1.048	0.027	1.007	1.081	17493	8931
delta_ GNI_ GNI_lag1[2012]	1.024	0.026	0.984	1.054	16574	9069
delta_ GNI_ GNI_lag1[2013]	1.023	0.025	0.985	1.054	16936	9200
delta_ GNI_ GNI_lag1[2014]	1.041	0.025	1.002	1.071	17291	9133
delta_ GNI_ GNI_lag1[2015]	1.050	0.024	1.013	1.080	16925	9216
delta_ GNI_ GNI_lag1[2016]	1.072	0.025	1.035	1.103	14888	9600
delta_ GNI_ GNI_lag1[2017]	1.027	0.022	0.994	1.054	16122	9388
delta_ GNI_ GNI_lag1[2018]	1.038	0.021	1.006	1.063	16748	8986
delta_ GNI_ GNI_lag1[2019]	1.030	0.021	0.998	1.054	16837	9337
delta_ GNI_ GNI_lag1[2020]	0.992	0.021	0.960	1.017	14800	9070
delta_ GNI_ GNI_lag1[2021]	1.029	0.021	0.996	1.054	16034	9291
delta_ GNI_ GNI_lag1[2022]	1.022	0.021	0.988	1.048	16030	9597
delta_ GNI_MFII_lag1[2010]	-16.773	23.504	-56.053	19.247	29144	24567
delta_ GNI_MFII_lag1[2011]	-12.294	21.217	-51.668	17.083	34400	29079
delta_ GNI_MFII_lag1[2012]	-16.386	19.613	-49.193	14.563	39348	33075
delta_ GNI_MFII_lag1[2013]	-16.644	18.069	-47.223	12.176	43530	37826
delta_ GNI_MFII_lag1[2014]	-16.029	16.759	-44.079	10.989	48086	40088

delta_ GNI_MFII_lag1[2015]	-16.498	16.413	-43.860	9.847	46602	41568
delta_ GNI_MFII_lag1[2016]	-12.111	16.062	-42.771	9.649	44972	40868
delta_ GNI_MFII_lag1[2017]	-15.270	15.533	-41.021	9.755	50027	43842
delta_ GNI_MFII_lag1[2018]	-12.285	15.285	-37.266	12.827	52643	43797
delta_ GNI_MFII_lag1[2019]	-11.132	15.511	-36.461	14.229	52045	42725
delta_ GNI_MFII_lag1[2020]	-12.192	15.627	-38.006	13.228	52217	42174
delta_ GNI_MFII_lag1[2021]	-10.917	16.039	-36.976	15.244	53236	42870
delta_ GNI_MFII_lag1[2022]	-10.130	16.784	-37.407	17.513	55713	44372
delta_MFII_ GNI_lag1[2010]	0.000	0.000	-0.001	0.000	28398	33099
delta_MFII_ GNI_lag1[2011]	0.000	0.000	-0.001	0.000	28976	33317
delta_MFII_ GNI_lag1[2012]	0.000	0.000	-0.001	0.000	27295	33317
delta_MFII_ GNI_lag1[2013]	0.000	0.000	-0.001	0.000	27101	33426
delta_MFII_ GNI_lag1[2014]	0.000	0.000	-0.001	0.000	27874	34047
delta_MFII_ GNI_lag1[2015]	0.000	0.000	-0.001	0.000	27761	33716
delta_MFII_ GNI_lag1[2016]	0.000	0.000	-0.001	0.000	28468	34514
delta_MFII_ GNI_lag1[2017]	0.000	0.000	-0.001	0.000	28503	34153
delta_MFII_ GNI_lag1[2018]	0.000	0.000	-0.001	0.000	30377	35162
delta_MFII_ GNI_lag1[2019]	0.000	0.000	-0.001	0.000	30900	35578
delta_MFII_ GNI_lag1[2020]	0.000	0.000	-0.001	0.000	31860	33724
delta_MFII_ GNI_lag1[2021]	0.000	0.000	-0.001	0.000	32010	35559
delta_MFII_ GNI_lag1[2022]	0.000	0.000	-0.001	0.000	30921	36297
delta_MFII_MFII_lag1[2010]	0.611	0.164	0.342	0.871	19815	26331
delta_MFII_MFII_lag1[2011]	0.618	0.151	0.367	0.859	20920	31213
delta_MFII_MFII_lag1[2012]	0.634	0.147	0.392	0.874	20833	32214
delta_MFII_MFII_lag1[2013]	0.635	0.140	0.400	0.862	19891	31259
delta_MFII_MFII_lag1[2014]	0.613	0.131	0.390	0.820	19547	32913
delta_MFII_MFII_lag1[2015]	0.620	0.132	0.395	0.826	19567	33856
delta_MFII_MFII_lag1[2016]	0.599	0.127	0.381	0.795	21043	34205
delta_MFII_MFII_lag1[2017]	0.598	0.126	0.381	0.794	22146	34586
delta_MFII_MFII_lag1[2018]	0.581	0.127	0.364	0.780	23303	33810
delta_MFII_MFII_lag1[2019]	0.571	0.132	0.345	0.775	24657	34030
delta_MFII_MFII_lag1[2020]	0.572	0.134	0.344	0.782	26543	34019
delta_MFII_MFII_lag1[2021]	0.580	0.136	0.352	0.796	28945	35737
delta_MFII_MFII_lag1[2022]	0.592	0.141	0.357	0.815	30434	38300
nu_ GNI_alpha_Burundi	-0.105	10.598	-15.341	13.128	21973	12149
nu_ GNI_alpha_DRC	-0.666	9.640	-14.460	10.520	18851	11110
nu_ GNI_alpha_Kenya	2.260	15.306	-2.225	30.003	15070	9244
nu_ GNI_alpha_Rwanda	-2.629	12.284	-22.682	11.275	17949	10726
nu_ GNI_alpha_Tanzania	0.926	8.589	-9.186	13.202	20639	12942
nu_ GNI_alpha_Uganda	-3.822	7.912	-15.854	5.024	21908	16464
nu_MFII_alpha_Burundi	-0.036	0.174	-0.327	0.229	21733	13966
nu_MFII_alpha_DRC	-0.056	0.174	-0.372	0.190	22299	13752
nu_MFII_alpha_Kenya	-0.033	0.169	-0.309	0.239	18546	13689
nu_MFII_alpha_Rwanda	0.006	0.173	-0.279	0.284	25813	25691
nu_MFII_alpha_Tanzania	0.078	0.149	-0.123	0.344	15197	13011
nu_MFII_alpha_Uganda	0.042	0.188	-0.235	0.363	15730	14001
sigma_GNI	17.643	1.791	14.983	20.825	28005	29524
sigma_MFII	0.092	0.009	0.078	0.109	29693	33869
sigma_nu_ GNI_alpha	10.091	12.961	0.686	31.033	9464	8715
sigma_nu_MFII_alpha	0.194	0.168	0.018	0.508	11004	12652
tau_ GNI_ GNI_lag1	0.017	0.005	0.009	0.026	14285	17067
tau_ GNI_MFII_lag1	3.653	3.173	0.261	9.805	24348	24374
tau_MFII_ GNI_lag1	0.000	0.000	0.000	0.000	19208	19484
tau_MFII_MFII_lag1	0.023	0.019	0.002	0.060	21286	23376
tau_alpha_GNI	2.668	2.286	0.191	7.105	25083	24352
tau_alpha_MFII	0.028	0.016	0.004	0.057	13209	15823

b. *Results from the model with G-20 financial inclusion indicators*

Parameter	mean	SD	LCI	UCI	bulk ESS	Tail ESS
beta_GNI_AnnualInflation	-0.052	0.370	-0.660	0.558	62213	34334
beta_GNI_UnEmploymentRate	1.955	1.374	0.279	4.296	16217	7758
beta_MFIIG20_AnnualInflation	0.000	0.001	-0.002	0.002	40249	35470
beta_MFIIG20_EYS	0.111	0.044	0.040	0.182	36068	37551
beta_MFIIG20_FemaleLFP15_64	0.006	0.006	-0.004	0.017	21791	33288
beta_MFIIG20_LEXP	0.026	0.020	-0.010	0.057	10618	14236
beta_MFIIG20_MYS	0.069	0.041	0.004	0.137	22761	28763
beta_MFIIG20_NumInternetUsers	0.000	0.003	-0.005	0.004	21475	13624
beta_MFIIG20_PopDensity	-0.001	0.001	-0.002	0.000	13354	17523
beta_MFIIG20_UnEmploymentRate	-0.002	0.011	-0.020	0.016	47485	16620
beta_MFIIG20_broadmoney	0.003	0.003	-0.002	0.008	25721	30484
alpha_GNI[2010]	-16.411	20.996	-43.580	15.442	20433	10656
alpha_GNI[2011]	-15.291	20.817	-41.746	16.469	20181	10395
alpha_GNI[2012]	-15.538	20.876	-42.032	12.178	19713	10585
alpha_GNI[2013]	-16.576	21.101	-43.546	15.567	19726	10508
alpha_GNI[2014]	-17.724	21.323	-45.279	15.092	19942	10550
alpha_GNI[2015]	-20.388	21.882	-49.805	13.110	19981	10665
alpha_GNI[2016]	-22.043	22.409	-52.954	12.068	19462	10479
alpha_GNI[2017]	-21.882	22.263	-52.410	12.092	19887	10288
alpha_GNI[2018]	-19.856	22.137	-49.896	14.278	19694	10966
alpha_GNI[2019]	-18.904	22.483	-49.372	16.035	19817	11206
alpha_GNI[2020]	-19.687	22.839	-51.215	15.815	20310	11190
alpha_GNI[2021]	-18.767	23.065	-50.611	17.371	20539	11223
alpha_GNI[2022]	-18.382	23.648	-51.455	18.839	20787	11304
alpha_MFIIG20[2010]	-3.073	1.616	-5.612	-0.267	10947	15509
alpha_MFIIG20[2011]	-3.060	1.622	-5.607	-0.243	10902	15382
alpha_MFIIG20[2012]	-3.030	1.635	-5.593	-0.186	10829	15048
alpha_MFIIG20[2013]	-3.021	1.642	-5.593	-0.162	10806	14898
alpha_MFIIG20[2014]	-3.003	1.654	-5.590	-0.117	10770	13974
alpha_MFIIG20[2015]	-2.998	1.660	-5.589	-0.100	10759	14017
alpha_MFIIG20[2016]	-2.999	1.664	-5.595	-0.091	10775	13942
alpha_MFIIG20[2017]	-2.979	1.674	-5.590	-0.047	10718	14024
alpha_MFIIG20[2018]	-2.957	1.686	-5.581	-0.002	10635	14205
alpha_MFIIG20[2019]	-2.958	1.688	-5.581	-0.003	10641	14334
alpha_MFIIG20[2020]	-2.950	1.690	-5.575	0.010	10627	14248
alpha_MFIIG20[2021]	-2.955	1.687	-5.576	-0.006	10668	14206
alpha_MFIIG20[2022]	-2.952	1.692	-5.579	0.011	10653	14389
corr_nu_MFIIG20_alpha__GNI_alpha	-0.140	0.571	-0.933	0.847	33011	30296
delta_GNI_GNI_lag1[2010]	1.052	0.032	1.004	1.090	16293	7762
delta_GNI_GNI_lag1[2011]	1.051	0.030	1.007	1.085	16028	7463
delta_GNI_GNI_lag1[2012]	1.024	0.028	0.984	1.055	15982	7741
delta_GNI_GNI_lag1[2013]	1.021	0.027	0.983	1.050	15784	7836
delta_GNI_GNI_lag1[2014]	1.036	0.026	0.999	1.065	16407	7399
delta_GNI_GNI_lag1[2015]	1.046	0.025	1.010	1.074	16195	7795
delta_GNI_GNI_lag1[2016]	1.066	0.025	1.030	1.096	15579	7825
delta_GNI_GNI_lag1[2017]	1.025	0.023	0.993	1.052	16051	7688
delta_GNI_GNI_lag1[2018]	1.038	0.022	1.006	1.063	15778	8032
delta_GNI_GNI_lag1[2019]	1.031	0.022	1.000	1.055	15180	7628
delta_GNI_GNI_lag1[2020]	0.994	0.021	0.963	1.019	14343	7546
delta_GNI_GNI_lag1[2021]	1.031	0.022	0.999	1.056	15170	7439
delta_GNI_GNI_lag1[2022]	1.025	0.021	0.994	1.050	16358	7527
delta_GNI_MFIIG20_lag1[2010]	13.830	42.089	-52.180	82.077	28584	25336
delta_GNI_MFIIG20_lag1[2011]	14.267	38.027	-46.301	76.363	31714	27493

delta_GNI_MFIIG20_lag1[2012]	14.839	35.448	-41.767	73.815	34260	29307
delta_GNI_MFIIG20_lag1[2013]	14.481	32.819	-38.573	68.798	36696	37737
delta_GNI_MFIIG20_lag1[2014]	13.751	30.952	-36.387	64.894	39145	37515
delta_GNI_MFIIG20_lag1[2015]	10.285	29.197	-38.133	57.449	39839	38360
delta_GNI_MFIIG20_lag1[2016]	9.833	28.273	-36.960	55.660	39862	41569
delta_GNI_MFIIG20_lag1[2017]	6.806	28.519	-41.068	52.524	37190	37307
delta_GNI_MFIIG20_lag1[2018]	9.600	26.909	-34.554	53.390	38319	35602
delta_GNI_MFIIG20_lag1[2019]	11.607	26.042	-30.949	54.244	40429	41839
delta_GNI_MFIIG20_lag1[2020]	11.581	26.529	-32.114	54.632	38649	34385
delta_GNI_MFIIG20_lag1[2021]	14.222	26.651	-29.153	57.947	36493	34434
delta_GNI_MFIIG20_lag1[2022]	14.733	27.800	-30.186	60.198	40178	36198
delta_MFIIG20_GNI_lag1[2010]	0.000	0.000	-0.001	0.000	42489	37990
delta_MFIIG20_GNI_lag1[2011]	0.000	0.000	-0.001	0.000	42437	38757
delta_MFIIG20_GNI_lag1[2012]	0.000	0.000	-0.001	0.000	42215	38961
delta_MFIIG20_GNI_lag1[2013]	0.000	0.000	-0.001	0.000	42345	38657
delta_MFIIG20_GNI_lag1[2014]	0.000	0.000	-0.001	0.000	43011	39287
delta_MFIIG20_GNI_lag1[2015]	0.000	0.000	-0.001	0.000	43241	39474
delta_MFIIG20_GNI_lag1[2016]	0.000	0.000	0.000	0.000	43798	40108
delta_MFIIG20_GNI_lag1[2017]	0.000	0.000	0.000	0.000	43272	40691
delta_MFIIG20_GNI_lag1[2018]	0.000	0.000	0.000	0.000	41995	40493
delta_MFIIG20_GNI_lag1[2019]	0.000	0.000	0.000	0.000	41699	41512
delta_MFIIG20_GNI_lag1[2020]	0.000	0.000	0.000	0.000	42022	41424
delta_MFIIG20_GNI_lag1[2021]	0.000	0.000	0.000	0.000	41080	40592
delta_MFIIG20_GNI_lag1[2022]	0.000	0.000	0.000	0.000	40454	41198
delta_MFIIG20_MFIIG20_lag1[2010]	0.371	0.171	0.092	0.652	28235	29461
delta_MFIIG20_MFIIG20_lag1[2011]	0.370	0.164	0.103	0.641	28451	33830
delta_MFIIG20_MFIIG20_lag1[2012]	0.375	0.160	0.115	0.640	28593	33462
delta_MFIIG20_MFIIG20_lag1[2013]	0.372	0.155	0.119	0.628	28442	32249
delta_MFIIG20_MFIIG20_lag1[2014]	0.374	0.152	0.126	0.627	28401	30626
delta_MFIIG20_MFIIG20_lag1[2015]	0.368	0.147	0.127	0.612	28674	27938
delta_MFIIG20_MFIIG20_lag1[2016]	0.362	0.147	0.123	0.605	28769	30736
delta_MFIIG20_MFIIG20_lag1[2017]	0.374	0.148	0.133	0.620	29838	32487
delta_MFIIG20_MFIIG20_lag1[2018]	0.376	0.149	0.134	0.624	28415	31793
delta_MFIIG20_MFIIG20_lag1[2019]	0.364	0.150	0.119	0.612	27789	31285
delta_MFIIG20_MFIIG20_lag1[2020]	0.374	0.150	0.130	0.624	29722	32833
delta_MFIIG20_MFIIG20_lag1[2021]	0.371	0.150	0.127	0.619	31146	32503
delta_MFIIG20_MFIIG20_lag1[2022]	0.376	0.155	0.125	0.632	31592	33833
nu_GNI_alpha_Burundi	-1.357	11.376	-16.576	11.728	23270	10931
nu_GNI_alpha_DRC	-0.877	9.918	-13.443	9.756	21447	9969
nu_GNI_alpha_Kenya	5.799	15.444	-5.723	28.819	14768	7553
nu_GNI_alpha_Rwanda	-2.754	12.297	-22.568	9.465	17161	8229
nu_GNI_alpha_Tanzania	1.549	8.288	-7.729	13.260	23032	10906
nu_GNI_alpha_Uganda	-2.664	7.514	-13.699	5.566	24761	15647
nu_MFIIG20_alpha_Burundi	0.267	0.246	-0.051	0.722	12867	18526
nu_MFIIG20_alpha_DRC	0.063	0.198	-0.265	0.390	19519	12107
nu_MFIIG20_alpha_Kenya	-0.195	0.222	-0.605	0.100	15001	17975
nu_MFIIG20_alpha_Rwanda	-0.129	0.216	-0.532	0.178	18994	11045
nu_MFIIG20_alpha_Tanzania	-0.213	0.193	-0.563	0.045	14155	17446
nu_MFIIG20_alpha_Uganda	0.204	0.241	-0.111	0.653	15021	19737
sigma_GNI	17.856	1.787	15.193	21.003	29668	27629
sigma_MFIIG20	0.053	0.005	0.045	0.062	22042	13707
sigma_nu_GNI_alpha	9.323	13.546	0.506	30.247	9601	6675
sigma_nu_MFIIG20_alpha	0.340	0.232	0.056	0.771	9188	12660
tau_GNI_GNI_lag1	0.016	0.005	0.009	0.026	14899	17885
tau_GNI_MFIIG20_lag1	5.870	5.294	0.384	12.114	26587	25735
tau_MFIIG20_GNI_lag1	0.000	0.000	0.000	0.000	27230	26325

tau_MFIIG20_MFIIG20_lag1	0.018	0.016	0.001	0.049	20245	22477
tau_alpha_GNI	2.871	2.421	0.212	7.558	27708	26803
tau_alpha_MFIIG20	0.014	0.010	0.001	0.033	9896	12793

Note: In Appendix 3, the Rhat statistic was consistently below 1.01; therefore, it was not reported. The SD is standard deviation, LCI and UCI are lower and upper confidence intervals at the 5% level of significance, bulk-ESS is Bulk Effective Sample Size, and tai-ESS is Tail Effective Sample Size.

ENDNOTES

[i] The EAC includes Burundi, the Democratic Republic of Congo (DRC), Kenya, Rwanda, Somalia, South Sudan, Tanzania, and Uganda.

[ii] Some studies use gross national income (GNI) per capita to measure economic growth or welfare. The GNI per capita differs from Gross Domestic Product (GDP) per capita and measures income earned by a country's residents rather than income generated by the country's production activities. However, GNI is suited for comparisons over time, as price changes also influence economic growth.

[iii] https://data.imf.org/?sk=E5DCAB7E-A5CA-4892-A6EA-598B5463A34C&sId=1412015057755

[iv] The Group of Twenty (G-20) is a forum for international economic cooperation between the world's leading economies. The G-20 aims to address global economic issues and strengthen the international monetary system. The G-20 consists of 19 countries and two regional bodies: the African Union and the European Union. The 19 countries are Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Türkiye, the United Kingdom, and the United States.

[v] https://databank.worldbank.org/databases , https://unctadstat.unctad.org/datacentre, https://data-explorer.oecd.org, and https://ilostat.ilo.org/data/.

[vi] See World Bank Definition at: https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html.