Exploring the Dynamics of Financial Inclusion for Vulnerable Populations Amidst a Global Pandemic

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Introduction

This research project focuses on the impact of the COVID-19 pandemic on financial inclusion for women and low-income adults across various countries. Financial inclusion, a crucial driver of economic stability and individual well-being, gained increased significance during the pandemic due to the vulnerabilities exposed by job losses, economic downturns, and lockdowns.

Prior to the pandemic, many emerging economies were making progress in financial inclusion, expanding access to banks, credit, digital payments, and financial technology innovations (Watkins et al., 2023). Advocates for global investments in comprehensive financial solutions emphasised the need to protect vulnerable populations in developing economies, especially those reliant on informal incomes, from income fluctuations (Watkins et al., 2023). However, there is a notable knowledge gap regarding how financial inclusion fared for disadvantaged groups during a global crisis (The World Bank, 2023). This project aims to address that gap by answering our project question:

"What was the state of financial inclusion for women and adults with low income in different countries pre and during the first year of COVID-19 pandemic"

This study is significant for several reasons. Firstly, it addresses the intersection of financial inclusion and public health by examining the experiences of marginalised groups during a global crisis, offering evidence-based insights for policy decisions and targeted interventions.

Secondly, it offers insights into the resilience of financial systems and the adaptability of financial inclusion strategies in the face of a global crisis, contributing to preparedness for future emergencies.

Lastly, the study highlights the importance of global collaboration and solidarity, emphasising the need for inclusive development in times of crisis. It contributes to a collective understanding of how financial inclusion can support vulnerable populations during emergencies.

Our research project incorporates various competencies, statistical, and computational sciences, guided by our Advisor, Dr. Arindam Basu (Hoodbhoy et al., 2023).

We aim for our findings to inform policy decisions and inspire a commitment to building more inclusive and resilient societies, where financial inclusion benefits are accessible to everyone, regardless of their economic status or gender.

The prospects of this project were promising, and we encountered no constraints in collaboration with our academic Advisor.

Data

The Global Findex Database (GFD), maintained by the World Bank since 2011, is a key resource for understanding global FI (FI) trends. It compiles extensive FI data from surveys conducted in numerous countries, covering around 150,000 adults across 144 countries. The dataset includes 658 observations on 1,232 FI-related variables, offering a comprehensive framework to assess financial services utilisation, payment transactions, savings, borrowing behavior, and financial event management among adults aged 15 and above (Watkins et al., 2023).

Surveys conducted in 2011, 2014, 2017, and the 2021 iteration provide updated insights into access to and usage of both formal and informal financial services. These insights cover various data types, including digital payments, demographics, FI metrics, debit and credit card ownership, borrowing activities, and more. Data collection occurred every three years but experienced delays, especially in the lead-up to 2021, due to the COVID-19 pandemic (The World Bank, 2023). Earlier iterations used face-to-face surveys with a nationally representative sampling of the civilian population aged 15 and above. In 2021, phone-based surveys replaced face-to-face methods to comply with global pandemic-related regulations (The World Bank, 2023). Notably, during the pandemic, the GFD saw increased digital merchant and utility payment adoption, shedding light on behavioural aspects of financial adaptability and disparities in financial services among women and low-income adults (The World Bank, 2023).

The World Bank's Development Data Group plays a crucial role in coordinating statistical and data operations, emphasising the importance of national statistical systems in data provision and capacity building in developing nations (The World Bank, 2023). This includes supporting statistical infrastructure, formulating national statistical strategies, and collaborating with international organisations to enhance data collection, analysis, and dissemination.

Data missingness in the GFD refers to the absence of recorded data for a specific variable within an observation, which can impact data inferences (Wikipedia, 2023). Missing data can occur for various reasons, including non-responses from survey participants due to privacy concerns, limited resources, and data entry errors.

Missing-not-at-random (MNAR) indicates a systematic and non-random pattern in missing data, often associated with unobserved factors (Wikipedia, 2023). For example, lower FI rates in survey non-responses could result in MNAR. In our analysis, we replaced 'Not Available' values with '0', creating an overall 'FI index' for countries in 2017 and 2021. This approach determined weights for the FI status using the most informative variables (Watkins et al., 2023).

Data quality validation involves investigating outliers for their potential causes and effects (Sullivan et al., 2021). We examined raw datasets, visualised the FI Index (Findex) rates by country region for General, Women, and Low-Income adults, and categorised countries by region using the World Bank country classifications for 2022-2023 (Hamadeh et al., 2022).

The raw dataframes used for our focus population groups in the visualisation are contained in Table 1. These dataframes consist of countries with their indicated regions, year, and the mean Findex. We categorised all countries within the General, Women, and Low-Income Adults' dataframes according to their respective regions, using the New World Bank country classifications by income level for the years 2022-2023 (Hamadeh et al., 2022). We also acknowledged that these regional classifications include economies at various income levels.

Table 1. Countries categorised by Regions for all focus populations in 2017 & 2021.

Data Frame Name	Snippet	Description	Data Types
mean_index_region_no_na	region / year / mean_fin_in south asia 2017 0.27381432 south asia 2021 0.27292247	Mean Findex scores of each country categorized by their respective regions based on the General population in years 2017 and 2021.	Character & Numeric
mean_index_region_women_no_na	region / year / mean_fin_in nothern america 2017 1.85842910 nothern america 2021 1.55823877		Character & Numeric
mean_index_region_poorest_no_na	region / year / mean_fin_in europe central asia 2017 0.39915916 europe central asia 2021 0.32074204		Character & Numeric

To perform our analysis, we utilised the 'plotly' package for creating interactive visualisations, including boxplots to identify univariate outliers (RDocumentation, 2023). We observed that the Sub-Saharan Africa region tended to present potential outliers for all three focus population groups, as shown in Figures 1, 2, & 3, with a summary of the distribution values in Table 2.

Values for those outliers across the focus population groups:

- General population during (2017 was 1.054 Namibia & 2021 was 0.884 South Africa)
- Women population during (2017 was 1.004 Namibia & 2021 was 0.880 South Africa)
- Low-Income adults during (2017 was 0.860 Namibia & 2021 was 0.827 Mauritius)

Assessing these outliers can help reinforce the data quality and provide insights into why countries like Namibia, South Africa, and Mauritius had extremely high mean Findex scores in the Sub-Saharan region compared to other countries within it. Instead of removing or transforming the identified outliers, we chose to investigate them further, as they can provide valuable information. A study by Allen et al. (2014) has shown that the countries Namibia, South Africa, and Mauritius have exceeded the predicted levels of FI, confirming the findings in our boxplots. Thus, one potential benefit of retaining these outliers in the data is the ability to compare FI regulations between countries, enabling us to determine the requirements necessary for fostering better financial inclusivity in each country.

The disparities within our classification class raw datasets were detected during data processing for our three studied population groups. We figured that class imbalance would be an example of categorising the countries' decrease and increase in its Findex score from 2017 to 2021. It may introduce imbalances where one class (decrease) significantly outweighs the other (increase) due to disparities in financial access across countries and regions. To identify imbalances in our data, we employed the 'mutate' function from the dplyr package, analysing changes in Findex scores from 2017 to 2021 in various countries (RDocumentation, 2023). Subsequently, we created a new variable column based on this information and removed all missing values (NAs). We employed the 'filter' function from the dplyr package to gather countries with two distinct Findex score classifications, merging them with the 'merge' function (RDocumentation, 2023). Following data preparation, we analysed the distribution of changes in Findex scores for General, Women, and Low-Income Adult populations.

While visually examining the data, we observed substantial disparities in the two distinct Findex score classes among the three focus population groups, as illustrated in Figures 4, 5, & 6. This underscores global class imbalances in Findex scores across three population groups from 2017 to 2021. Table 2 reveals that in the General population, 14.16% of countries increased their Findex scores, while 85.84% experienced a decrease. Among the Women population, 15.05% saw an increase, compared to an 84.95% decrease. Lastly, the Low-Income adults group showed a 20.35% increase, with a 79.65% decrease in Findex score changes from 2017 to 2021.

Table 3: Total number of countries whose Findex scores changed from 2017 to 2021.

Change in Findex score	General Population	Women Population	Low-Income Population
	Total Number	**Total Number**	**Total Number**
Decreased	97	96	90
Increased	16	17	23

Class imbalances in our datasets can significantly impact data analysis outcomes and interpretations. Detecting these imbalances during data processing is crucial to avoid biases and limitations in our analysis results. For instance, the imbalance between countries showing Findex score decreases and those with increases from 2017 to 2021 may skew our findings and hinder predictive model accuracy. Addressing class imbalances through data pre-processing techniques is essential for reliable and generalisable findings, contributing to informed decision-making.

Notably, the 'Not Available' minimum and maximum values in Table 2 for the Northern America (NA) region are attributed to the region's small size, which consists of only three countries, leading to limited data variability. While this limitation is beyond our control, it serves as a research constraint and must be acknowledged when drawing inferences.

An unexpected issue emerged during data processing, involving a variable with near-zero variance in 2017. Upon investigation, we discovered that data for Iceland was missing from the 2017 records in the GFD, as documented by The World Bank (2023). An error in data entry occurred where all missing values (NAs) were mistakenly replaced with zeros, identified during Exploratory Data Analysis (EDA) when creating Figures 4, 5, and 6. To address this, we excluded Iceland from our datasets using the 'filter' function to improve interpretability of visualised graphs, ensuring the accuracy of our analysis.

Addressing these challenges enhances the transparency of our dataset's limitations, strengthening the credibility and reliability of our research findings.

Methodology

Data Retrieval and Pre-Processing -

The data for this research project was retrieved from the World Data Bank website, a reputable source for global financial data. The World Data Bank provides a comprehensive repository of economic and financial information, making it a suitable choice for our research needs (The World Bank, 2023). The data, crucial for assessing FI on a global scale, was downloaded in the widely used Excel file format, ensuring compatibility and ease of access.

The primary objective of the GDF is to gauge the extent of FI by assessing the utilisation of many different finance-related variables among individuals aged 15 years and above. By collecting data pertaining to financial behaviours, ownership of financial accounts, patterns of usage, etc., the database offers valuable insights into how individuals access and interact with formal and informal financial systems (The World Bank, 2023).

To efficiently analyse and manipulate the acquired dataset, we chose RStudio as our Integrated Development Environment (IDE) (DataCamp, 2022). This decision was influenced by our extensive experience with R programming from previous university courses, which makes RStudio a natural fit for our research workflow. RStudio offers a user-friendly interface, robust data manipulation capabilities, and a wide range of libraries and tools that enhance our ability to extract meaningful insights from the data (Grolemund, 2017).

Data Processing -

It is imperative to note that the explanation of the data processing and EDA steps below apply to each of our 3 focus populations which include: General, Women, and Low-Income Adults unless stated otherwise.

As part of our documentation and reporting strategy, we employed a Quartile Markdown file to record our data processing steps and analysis procedures. This Markdown file serves as a dynamic and interactive document that combines narrative explanations with embedded R code chunks (Grolemund, 2023). By utilising the Quartile package, we were able to create a well-structured report that seamlessly integrates text, code, and visualisations, allowing for easy reproducibility and collaboration with team members.

To leverage the GFD for our research, we employed a series of data processing and analysis steps using RStudio. First, we loaded essential R packages, including readxl, ggplot2, tidyverse, readr, stringr, visdat, skimr, highcharter, dplyr, and plotly, to facilitate data manipulation, visualisation, and analysis (Grolemund, 2023). We initiated the data processing by downloading the GFD into R and examining its contents. The dataset, named "DatabankWide" was imported from the Excel file mentioned above, and we used functions such as view() from utils package, class(), and str() to explore its structure and characteristics (RDocumentation, 2023). After importing, this initial data frame consisted of 314 observations and 1232 variables.

To ensure the dataset's relevance to our research objectives, we eliminated data for the years 2011, 2014, and 2022. This step was executed using the pipe operator in conjunction with the filter() function. The resulting dataset remained stored as "DatabankWide".

Principal Component Analysis (PCA) specifies the weights required to obtain new variables that account for the variation in an entire dataset. These new variables, including defining weights, are referred to as principal components (Bro, 2014).

Watkins et al. (2023), used World Bank metrics to create national FI indices. These indices were derived from PCA, which was based on 20 metrics from the latest available (2017) pre-pandemic panel. This panel includes indicators on access to and use of financial services and financial technologies, and the PCA revealed that the two main components with the largest eigenvalues accounted for over 71% of the overall variance across the 20 variables (Watkins et al, 2023).

Our project team drew on the influence of this work to extract 12 of the 20 specific indicators with highest eigenvalues according to the PCA. However, due to a lack of data on Women and Low-Income Adults, 3 of the initial 12 variables were swapped for additional variables that provided data on all three of our focus groups. This was done to ensure that our project had an accurate representation of all three focus populations.

Table 4. Components of the FI Index (Findex) Calculations.

Extracted Variables –	**Principal Component 1 or 2 -**
1. Financial institution account	1
2. Borrowed from a financial institution or credit card	1
3. Saved at a financial institution	1
4. Debit car ownership	1
5. Credit card ownership	1
6. Outstanding housing loan	1
7. Used the internet for online transactions	1
8. Made or received digital payments	1
9. Saved for old age	1
10. Borrowed for health or medical purposes	2
11. Borrowed from family or friends	2
12. Coming up with emergency funds in 7 days: possible	2

Table 4 shows the specific variables extracted and combined into a new dataset, named "comp1_df," which also included key variables such as country name, country code, etc. A key variable is an observation that is uniquely identified by a variable or a collection of variables (Grolemund, 2017). For example, in a straightforward situation, a single variable can uniquely identify an observation e.g. the country name column in the “comp1_df” can uniquely identify a country’s data.

To enhance the interpretability of our dataset, we undertook the task of renaming columns, ensuring more meaningful and consistent variable names. This process was facilitated by the rename() function from from dplyr package, transforming variable names such as "Financial institution account (% age 15+)" to "financial_account" and "Coming up with emergency funds in 7 days: possible (% age 15+)" to "creating_possible_emergency_funds" (RDocumentation, 2023).

To handle missing data, we systematically replaced any missing values (NAs) in selected variables with zeros using the mutate() function, ensuring smooth calculations (Rimal, 2020).

Next, we created the "fin_inclusion_index," a composite measure of FI, by weighting and summing individual financial variables (Watkins et al., 2023). We'll interpret results using the Alliance for FI's (AFI) four FI categories (AFI, 2016):

1. High FI: Findex Score > 0.75
2. Above-average FI: 0.5 ≤ Findex Score < 0.75
3. Moderate FI: 0.25 ≤ Findex Score < 0.5
4. Low FI: Findex Score < 0.25

In conclusion, our RStudio data processing resulted in three refined datasets for our focus populations, forming the foundation for our in-depth analytical investigations into FI dynamics.

Exploratory Data Analysis -

We have broken the Exploratory Data Analysis (EDA) section of our report into 4 tasks describing the methodology behind each visualisation. These tasks included:

1. Region Boxplots
2. Income Group Boxplots
3. Slope Charts
4. Bubble Charts & Linear Regression Analysis

In our EDA section, we initiated by comparing Findex scores for 2017 and 2021 within the General, Women, and Low-income Adult data frames. While the 'DatabankWide' data frame included a region column, we discovered inaccuracies, such as Australia's region observation being 'High Income' instead of 'East Asia & Pacific.' Consequently, we manually created new data frames for the 7 regions following the New World Bank definitions, aligning each country with its corresponding region (Hamadeh et al., 2022). These individual data frames were consolidated using the bind_rows() function from the dplyr package, aligning them vertically by columns (RDocumentation, 2023).

To prepare the Findex score datasets, we utilised the na.omit() function, eliminating missing values. This was crucial as missing scores for 2017 or 2021 rendered countries unusable for meaningful comparisons. After data wrangling, we merged the Region and Findex datasets using the inner_join() function from the dplyr package, creating distinct index-region data frames tailored to each focus population (RDocumentation, 2023).

We employed boxplots to comprehensively understand Findex score changes between 2017 and 2021. These visualisations showcased score distributions by region and year, facilitating a direct comparison of Findex levels before and during the pandemic. By using the ggplotly() function from the plotly package, we generated interactive box plots (RDocumentation, 2023). These boxplots, represented by specific regions, provided insights into the data's central tendency. Scatter plot points overlaid on the boxplots added clarity to mean values for each region-year combination. Subsequently, we opted for a grouped boxplot encompassing all focus populations, allowing for a focused examination of Women and Low-Income population's recent FI status (RDocumentation, 2023). These boxplots were instrumental in visualising population-specific outliers and identifying similarities and differences.

For our second EDA task, we aimed to assess Findex scores for 2017 and 2021 across income groups within our focus populations. The 'DatabankWide' data set was extended by introducing an 'income_group' column with four categorical observations. Similar to our region analysis, we employed data manipulation techniques. We initiated by creating a new data frame, merging country names and income group data using the select() and rename() functions from the dplyr package (RDocumentation, 2023).

Next, we integrated this data with Findex scores for specific years using the inner_join() and distinct() functions from the dplyr package to remove duplicates. To reshape the data frame, we employed the pivot_wider() function from the tidyr package. Then, using the group_by() and summarise() functions from the dplyr package, we calculated average Findex scores for 2021 by income group (RDocumentation, 2023). Our final visualisation involved a grouped boxplot highlighting the 2021 Findex scores for each focus population.

Slope charts excel at comparing two instances, presenting changes over time in a clear and intuitive manner (Weitz, 2020). Our slope chart task consisted of visualising Findex scores for countries in each focus group between 2017 and 2021. We first categorised the countries as either "increasing" or "decreasing" in Findex scores using pivot_long() function from tidyr package, transforming the dataframe into a more appropriate format, and generating labels for countries with increasing scores (RDocumentation, 2023). Labelling all countries resulted in significant overlapping, making it difficult to discern data points by country. Therefore, we opted to label only the countries that experienced an increase in their Findex scores.

Another dilemma was having to filter out the country ‘Iceland’ due to the initial slope charts for all populations consisting of Iceland’s Findex score beginning at zero. We recognised this inaccuracy, as it is implausible for any country to begin a Findex score at zero. After checking the original ‘DatabankWide’ data frame, we realised we had set the NAs within the Iceland observation to zero instead of omitting the whole row as we had for all other countries. The resulting graph used line plots to show Findex score trends over the years 2017 & 2021, with text labels for increasing countries. This enables a time-based comparison of Findex score changes, categorised by change direction, and supports interactive display using ggplotly() for deeper exploration.

For task 4, we extracted relevant data from the "DatabankWide" data frame, including country names and population density, and merged it with the Findex score data for 2021. This process generated visualisations, including a bubble chart illustrating the relationship between population density and Findex scores for all countries. In the chart, bubble size corresponds to population size, and position is determined by the Findex score (Healy, 2022). This was complemented by a linear regression graph showing the trends in Findex scores in relation to changes in population sizes, as depicted in Figures 9, 10, and 11.

Data Ethics -

This research on the FI status during the COVID-19 pandemic, we prioritise ethical considerations related to the World Bank data we accessed. While the data from the Global Findex Database (GFD) did not contain sensitive individual-level information, we commit to anonymising any such data if necessary, to protect survey participants' privacy (Association for Computing Machinery, 2023). Our dedication to ethical data practices aligns with the World Bank Group's Personal Data Privacy policy, emphasising responsible data handling (World Bank Group policy, 2023). We also respect individuals' rights to access their personal data and seek redress, promoting transparency and ethical research conduct (Accountability Mechanism, 2023). Our research consistently upholds high ethical standards, guided by the World Bank Group's privacy policy.

Results

Region Group Analysis -

In Figure 7, we present the 'Mean FI Index across all Regions for all Population Groups in 2021'. The box plot graphic is a key component in our research, offering a visual summary of the mean Findex distributions for various regions and population groups in 2021. Boxplots are powerful tools for analysing data, revealing central tendencies and data spread (Jaggi, 2003). This figure illustrates FI variability across regions and population groups, emphasising differences in median values and data spread. It sets the stage for deeper exploration of disparities and trends in FI, contributing to a comprehensive understanding of our findings. Our goal is to identify regions with effective FI practices and enable comparisons with less effective regions, potentially facilitating the exchange of valuable information among governments to enhance the FI revolution.

Note that each region comprises a different number of countries. We opted not to alter this aspect because the boxplot's spread aids in determining a region's mean Findex score variation. Even in regions with numerous countries, if their mean Findex scores are similar, the boxplot's spread remains small, indicating limited data variability. An instance of this is evident in Figure 7's boxplot for Sub-Saharan Africa (SSA). SSA includes 48 countries according to the New World Bank country classification, signifying that most SSA countries had similar FI experiences in 2021, as indicated by the narrow spread of the boxplot (Hamadeh et al., 2022).

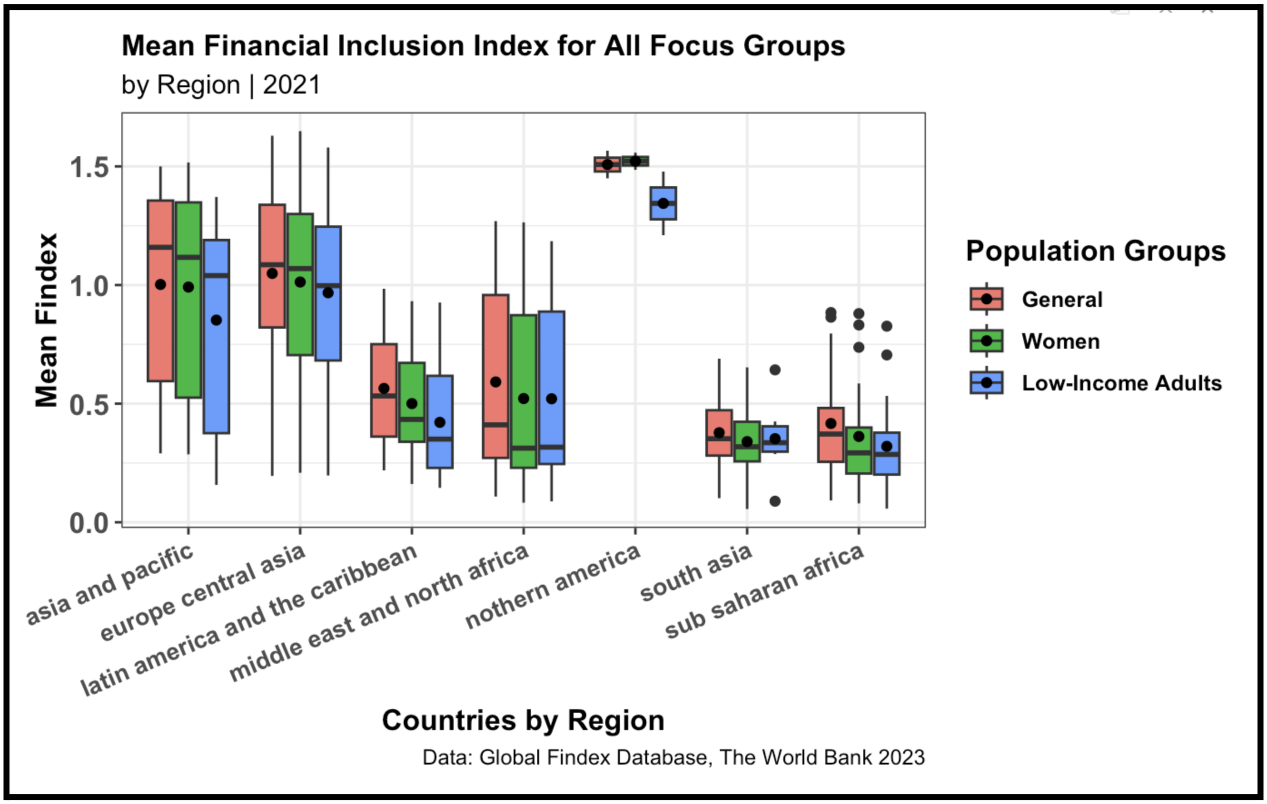
Conversely, in regions with multiple countries, diverse mean Findex scores among them result in a wider boxplot spread, reflecting greater variability in their FI initiatives. This signifies that some countries have experienced a more pronounced FI revolution than others. In Figure 7, East Asia and Pacific (EAP) exemplifies this with its 38 countries. The interquartile range in EAP displayed a more extended spread compared to SSA, indicating disparities in FI initiative development.

Currently, we've noted that all regions saw a decline in their mean Findex scores from 2017 to 2021, evident in Figures 1, 2, & 3. This observation has spurred a detailed investigation to pinpoint the regions with the highest and lowest mean Findex in 2021. We incorporated mean scores into Table 2 and Figure 7 to provide an overview of the central tendency of mean Findex for different regions and population groups in 2021. Table 2 complements Figure 7 by presenting summary statistics (Min, Q1, Median, Mean, Q3, Max) for 2021 across all focus groups, facilitating a comprehensive exploration of disparities and FI trends.

Figure 7 displays significant variations in mean Findex scores among regions and population groups. In 2021, South Asia (SA) and Sub-Saharan Africa (SSA) had the lowest mean Findex scores. For the General population, SA’s first and third quartiles ranged from 0.273 to 0.497, and SSA ranged from 0.244 to 0.490. In the Women population, SA's quartiles spanned from 0.252 to 0.443, while SSA ranged from 0.189 to 0.407. For the Low-Income population, SA's quartiles extended from 0.288 to 0.425, and SSA ranged from 0.194 to 0.385. Both regions exhibited a narrow interquartile range, indicating limited variability in mean Findex scores. This suggests that countries in these regions may have encountered challenges in advancing their FI initiatives.

Northern America stands out with the highest mean Findex scores among all regions. For the General population, the first and third quartiles range from 1.450 to 1.566, while for the Women population, quartiles range from 1.486 to 1.558. Lastly, for the Low-Income population, quartiles span from 1.210 to 1.478. This region exhibits the least variability in mean Findex scores compared to other regions, as indicated by its narrow interquartile range. This suggests that countries in this region had relatively consistent approaches to managing and developing their FI initiatives.

Figure 7. Mean FI Index across all Regions for all Population Groups in 2021



Income Group Analysis -

Figure 8 visualises the 'Mean FI Index for all focus populations in 2021 by income group,' categorising countries into four income levels: low income, lower middle income, upper middle income, and high income. This figure illustrates variations in FI across income groups, emphasising distinctions in data outliers, mean, median, quartiles, and minimum and maximum values. The goal is to promote the exchange of critical information among income groups, fostering awareness of income inequality and enhancing economic well-being concerning FI.

Upon analysis of Figures 18, 19, & 20, we observed that all income groups decreased their Findex scores for the years 2017 & 2021. Due to this, we decided to perform the same methodology as we did for the regional boxplots for further analysis. Hence, we grouped each focus population boxplot together to Findex scores during the year 2021. Table 5 and Figure 8 provide a summary of each income group and focus population mean Findex values.

Table 5. Findex mean values for Boxplots by Income Groups per Focus Population (2 s.f).

	Low Income	Lower Middle Income	Upper Middle Income	High Income
General	0.29	0.42	0.65	1.27
Women	0.25	0.38	0.59	1.24
Low-Income Adults	0.23	0.34	0.53	1.17

Figure 8. Grouped Boxplot on all Focused Groups by Income Level in 2021

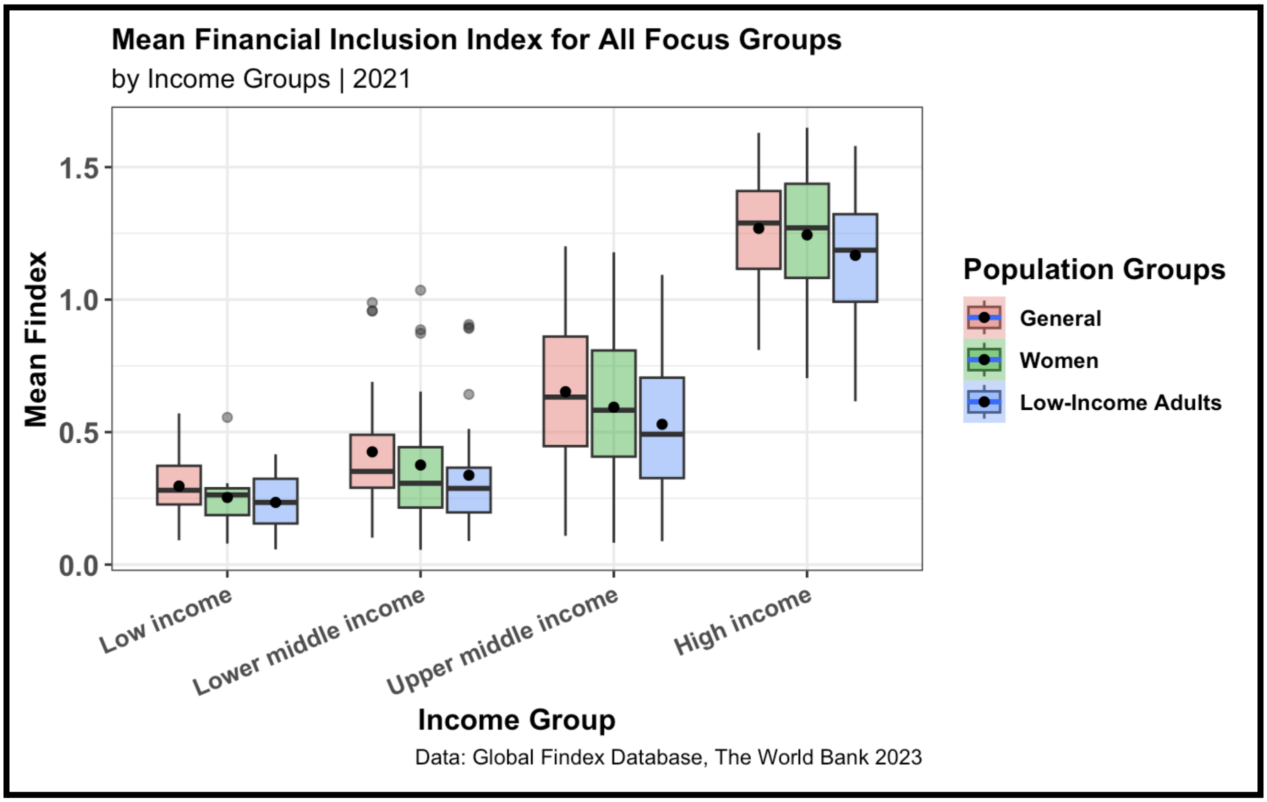


Table 5 reveals a consistent pattern in mean Findex scores across income groups. In each group, the General population consistently has the highest mean scores, followed by Women, and then Low-Income Adults. Notably, mean FI scores for the General population exhibit a clear upward trend with increasing income levels, ranging from lowest in Low-Income countries (0.29) to highest in High-Income countries (1.26), indicating a positive correlation between income and FI.

This trend is similarly observed in the Women population, with mean scores increasing with higher income levels: lowest in Low-Income countries (0.25) and highest in High-Income countries (1.24). Low-Income Adults also follow this pattern, with the lowest mean score in Low-Income countries (0.23) and the highest in High-Income countries (1.17).

These findings underscore a strong relationship between income groups and FI scores for all focus populations, highlighting that higher income levels are associated with higher mean FI scores. It's worth noting the presence of outliers within each population, significantly deviating from the mean scores of their respective groups.

Figure 8 highlights notable outliers in FI scores within different population groups. In the General population, Iran and Ukraine exhibit outlier scores of 0.96, while Mongolia has a slightly higher score of 0.99. Among the Women population, Iran has an outlier score of 0.87, Ukraine with 0.89, and Mongolia stands out with a substantially higher score of 1.04. This suggests that Mongolia may have implemented specific measures to promote FI among women.

In the Low-Income population, Iran stands out with an outlier score of 0.90, closely followed by Saudi Arabia with a score of 0.89. Sri Lanka, with a score of 0.64, also represents an outlier within this population. These countries significantly surpass the mean scores for their respective populations, indicating potential success in implementing policies or initiatives that enhance FI. Further examination of their strategies could offer valuable insights for improving FI in other nations.

Slope Chart Analysis -

Figures 4, 5, & 6 feature slope charts comparing Findex scores for the General, Women, and Low-Income Adults' populations in 2017 and 2021. Increasing Findex scores are shown in red lines, while decreasing scores are in blue. Each line is labeled with the corresponding country. These charts effectively illustrate the disparity between countries with increasing and decreasing Findex scores, providing a clear visual representation of the trend.

Analysing Figure 4, the General population slope chart, we observe 16 countries with increased Findex scores from 2017 to 2021. In this group, the European & Central Asian region (ECA) had the highest representation, with six countries.

Moving to Figure 5, the Women population slope chart, there are 17 countries with increased Findex scores from 2017 to 2021, and again, the ECA region had the most countries showing improvement.

Figure 6, which focuses on Low-Income Adults, reveals 23 countries with increased Findex scores during the same period, with the ECA region having the most representation.

In summary, when considering Findex score increases across General, Women, and Low-Income Adult populations, 14 countries experienced improvement. Unique increases were observed in the Philippines and Myanmar for the General population, Mongolia for the Women population, and seven countries, including Austria, Ireland, and Estonia, for Low-Income Adults. Additionally, Peru and Afghanistan saw Findex score increases in both Women and Low-Income Adult populations.

Table 6. Largest Findex Score Changes Across all Population Groups (2 s.f).

	Largest Increased	**Largest Decrease**
General	Bosnia & Herzegovina → 0.16 Increase	United Arab Emirates → -0.54 Decrease Lebanon → -0.42 Decrease
Women	Saudi Arabia → 0.20 Increase	United Arab Emirates → -0.39 Decrease Lebanon → -0.33 Decrease Iran, Islamic Rep. → -032 Decrease
Low-Income Adult	China → 0.24 Increase Brazil → 0.21 Increase	United Arab Emirates → -0.37 Decrease Lebanon → -0.33 Decrease Iran, Islamic Rep. → -0.34 Decrease

When looking at Table 6 within the General population, Bosnia & Herzegovina (B&H) demonstrated the largest Findex score increase, while the United Arab Emirates had the largest decrease, closely followed by Lebanon. Among Women, Saudi Arabia led in Findex score improvement, whereas the United Arab Emirates, Lebanon, and Iran, Islamic Rep as seen in Table 6 witnessed the most substantial decreases. Notably, these three countries belong to the MENA region. For Low-Income Adults, China showed the largest increase, followed closely by Brazil. Conversely, the United Arab Emirates experienced the most substantial decrease. Remarkably, three out of the top five countries with the largest decreases belonged to the MENA region, including Lebanon and Iran, Islamic Rep.

Overall, these findings suggest that the ECA region consistently outperformed others in improving FI across all three populations. With this being said, it is imperative to note that the data frame for this region contains 57 countries compared to Northern America which only contains 3 countries. This may raise concerns about representability and generalisability of the results. Based on the results in Table 6, there is an evident pattern of countries that had a large decrease in Findex scores all belonging to the MENA region. Further investigation into the specific policies and initiatives of these regions as well as countries such as Peru and Afghanistan, could provide insights into their success in enhancing FI.

Figure 5. Slope Chart of General Population comapring Country Findex Scores during 2017 & 2021.

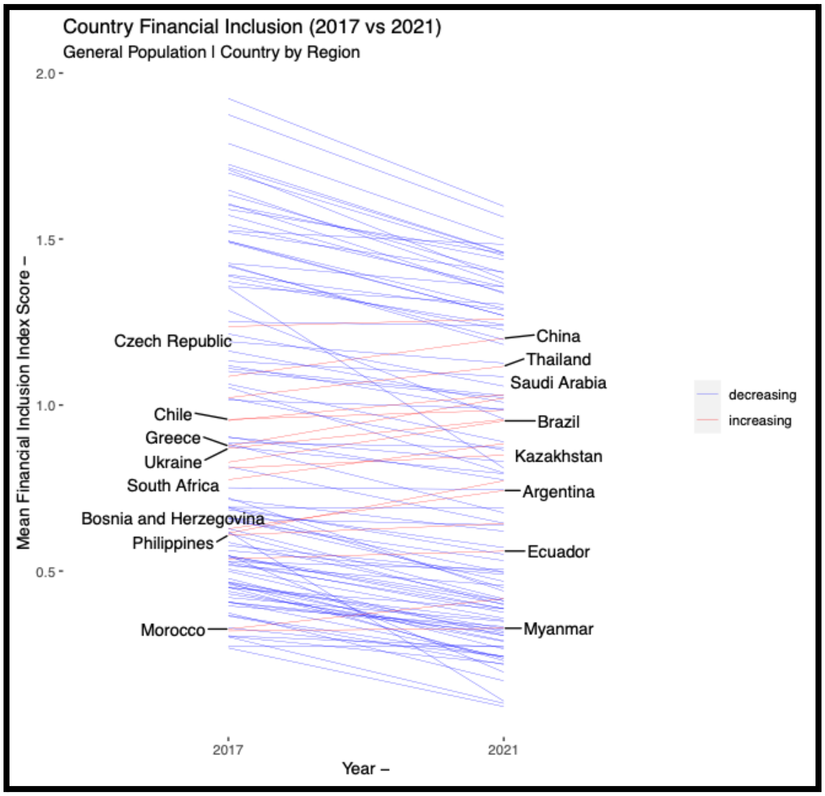
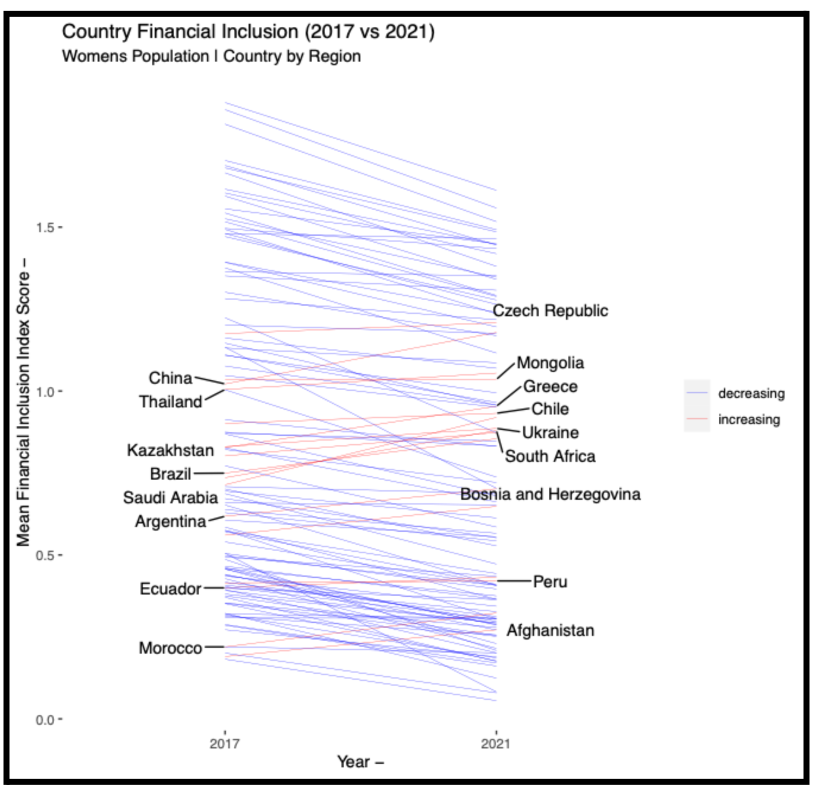


Figure 6. Slope Chart of Women Population comapring Country Findex Scores during 2017 & 2021.



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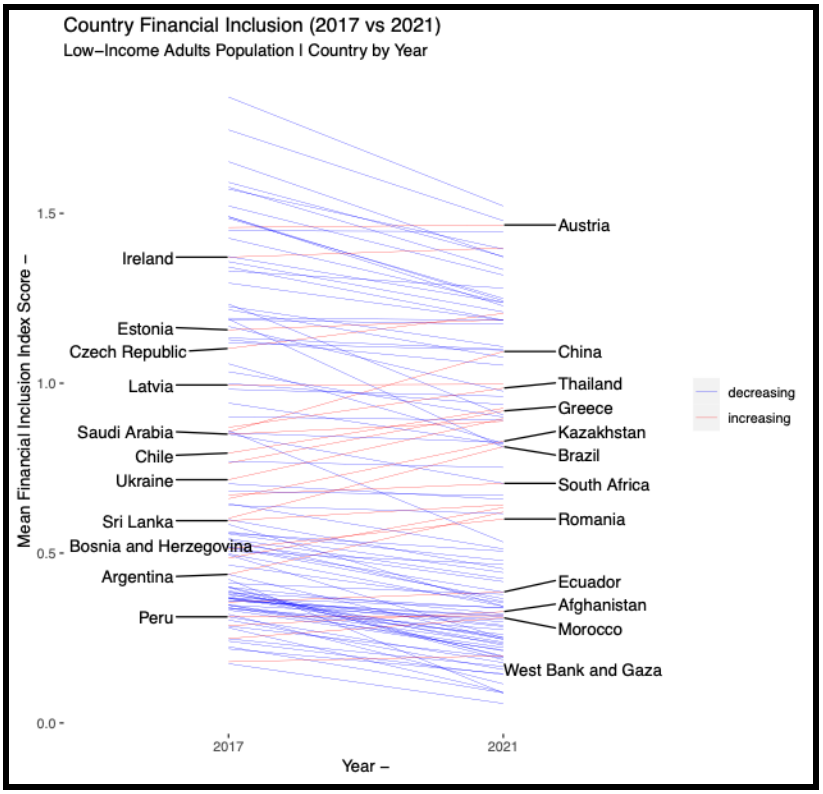


Bubble Charts and Linear Regression Analysis -

Linear regression analysis is a fundamental statistical method that we have employed in our research to uncover relationships and trends within our data. It enabled us to model the connection between Findex scores (y-axis) and population density metrics (x-axis) in various regions in 2021, yielding valuable insights. Each line length is dependent on the mass population of individual countries in different regions. Regions like East Asia and Pacific (EAP), containing China, and South Asia (AS), having India, are responsible for the length of the regression lines due to their populations exceeding one billion.

Additionally, we have created bubble charts (Figures 9, 10, & 11) to adjunct these linear regression graphs. For that reason, data points were not included in Figures 12, 13, & 14, as we used the bubble charts to represent individual countries and their population density for each bubble. Serving the same purpose of representing an insightful exploration of the correlation between Findex scores and population density of the three focus groups across different regions in 2021. Each bubble within these charts represents a specific country by region, with its size corresponding to the population mass, while its position on the chart reflects the Findex score.

Our analysis primarily focuses on Figures 13 and 14, as we aim to gain a deeper understanding of the 'FI state of Women and Low-Income individuals in different countries in 2017 compared to 2021.' Furthermore, due to the identified decrease in Findex scores from 2017 to 2021 from the Region and Income Group Analysis above, we will concentrate on analysing the results of Findex scores in relation to population density for the recent year of 2021.

The Women and Low-Income populations in Figures 13 and 14 showed different regression lines. When observing the EAP and SA regions, we notice a weak positive correlation between Findex scores and population density. The slope lines for these two regions remained nearly constant, indicating that countries in these regions, both for Women and Low-Income populations, showed a weak positive relationship. In other words, when individual countries increased their population, there was a slight increase in their FI services. Jahan et al. (2019) illustrate that some countries in regions EAP and SA fall behind in the FI revolution compared to other countries in the same regions like China, Malaysia, and Thailand where the FI revolution has expanded. This highlights significant disparities in access to financial services as the population growth continues, especially with regard to gender and income status among the population. It underscores the persistence of gender and income status disparities, with lower percentage of women and low-income individuals having access to formal financial tools compared to other demographic groups, particularly in these regions (Poghosyan, 2023).

Another finding from the analysis of Figures 13 and 14 pertains to the regions of Northern America (NA) and Middle East and North Africa (MENA) for both the Women and Low-Income populations. These regions exhibited a distinct pattern, revealing a moderate negative correlation between Findex scores and population density. Consequently, as the population density increased in countries within these regions, there was a tendency for a decrease in FI, indicating that higher population concentrations were associated with reduced access to Findex services. This finding sheds light on a unique dynamic in these regions, where the relationship between population density and FI differs from the general trends observed in other areas. It emphasises the need for region-specific policy considerations to address the challenges of expanding FI in densely populated regions like NA and the MENA. Studies by Eken et al. (1996) have argued that the rapid population growth in MENA countries has led to an increase in the high dependency ratio among individuals. Furthermore, this effect may slow economic growth in MENA countries, potentially affecting the FI revolution, especially for vulnerable groups like women and low-income individuals. In addition, a literature review by the United Nations (2020) highlighted the increasing income inequality observed in many developed countries, including those categorised as high-income nations. Notably, the countries within the NA region, such as Bermuda, Canada, and the United States, fall into the high-income category (Hamadeh et al., 2022). Hence, income disparities in these nations notably affect access to FI services for women and low-income populations. This situation tends to worsen as the population continues to grow, as depicted in Figures 13 and 14.

Finally, a strong positive correlation between Findex scores and population growth is evident in ECA, LAC, and SSA. Suggesting that population growth in countries within these regions correlates to an increase in the FI revolution, as seen in both graphs for Women and Low-Income populations. Expanding on this, we delve into the financial behaviours of individuals in these regions, showing that in high-income countries within ECA and LAC regions, many adults prefer using their formal accounts for wage payments. Conversely, in countries within the SSA region, many adults often use their accounts to receive funds sent by family members residing in different locations (Demirgüç-Kunt & Klapper, 2012). This informs us that Women and Low-Income adults have high access to FI services in these regions, and as the population grows, more individuals are accessing FI services.

Figures 12, 13, & 14, serve as powerful tools in our analytical toolkit. These figures showcased linear regression analyses, allowing us to delve into the extensive demographic implications of FI. They provided a gender-specific perspective on the correlation between Findex scores and demographic factors, and helped us dissect the FI landscape within regions. Through these linear regression graphs, we conducted a rigorous statistical analysis to uncover significant patterns, associations, and insights, ultimately leading to a deeper understanding of global FI dynamics.

Figure 12: Linear Regression between Findex scores of countries and General Population Density per Region in 2021.

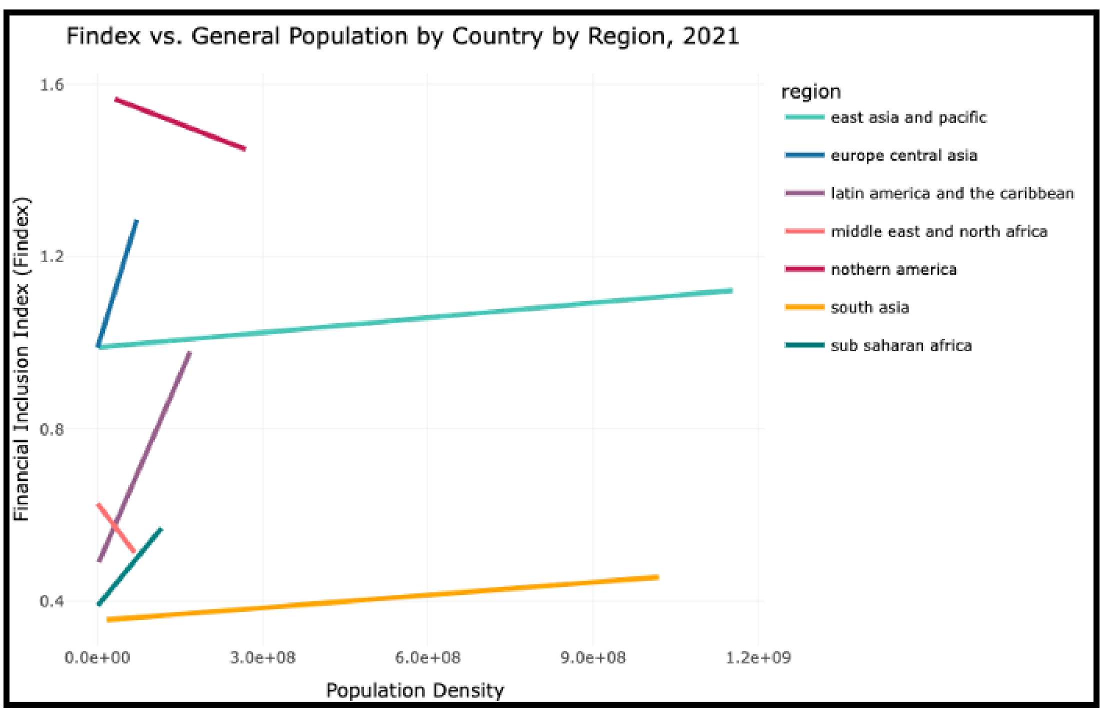


Figure 13. Linear Regression between Findex scores of Countries and Women Population Density per Region in 2021.

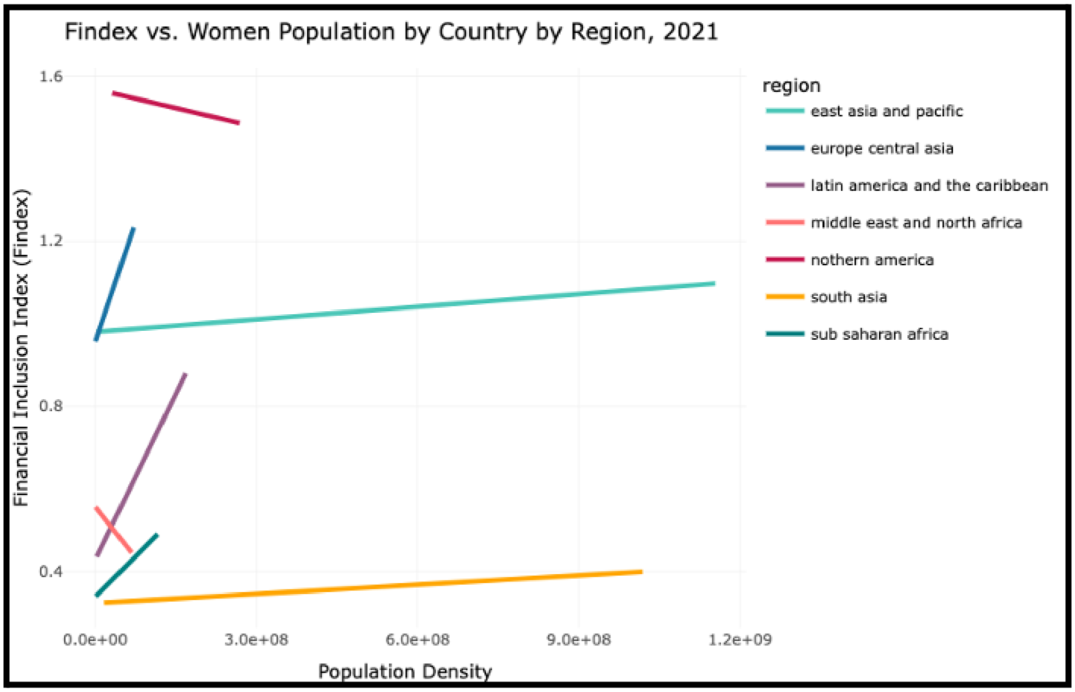
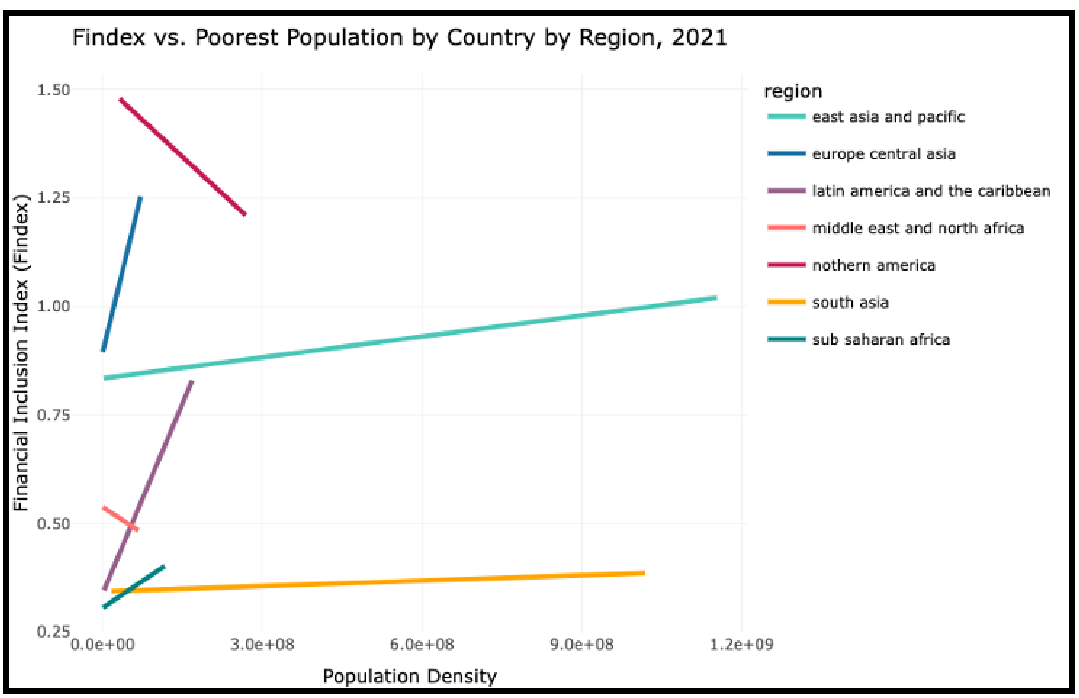


Figure 14. Linear Regression between Findex scores of Countries and Low-Income Population Density per Region in 2021.



Model -

We chose a linear regression model as our primary method in our research project, which assesses the FI status of women and low-income populations in various countries for 2017 and 2021. Our aim was to predict the 'fin_inclusion_index' (Findex Scores), calculated during data processing. These are a set of independent variables from the first and second Principal Components, described in Watkins et al. (2023).

From a pool of 20 metrics, we developed two indicators—one for formal financial tools and one for informal financial tools—to gauge the extent of each nation's population engaging in diverse financial services and activities (Watkins et al., 2023). During data processing, we retained 12 of these metrics, chosen for their high significant loading values in PC1 or PC2, as briefly outlined in the methodology.

To ensure the inclusivity of our model, we specifically considered three variables associated with the second principal component, referred to as ‘informal financial tools’. The remaining nine variables represented the first principal component, labelled as ‘formal financial tools’ (Watkins et al., 2023). This comprehensive approach, which incorporates these 20 metrics through Principal Component Analysis (PCA), enhances our model's performance by reducing the dataset's dimensionality while preserving its original variability.

Subsequently, we used these 12 metrics along with their respective PC loading values as a weight for calculations to allow us to assign varying degrees of importance to a single predictor, referred to as the ‘FI Index’, or simply ‘Findex’. This single indicator, Findex, provides a comprehensive overview of both formal and informal FI instruments, based on generalised assumptions about a country's progress in the implementation of the FI revolution.

Our linear regression analysis in 2021 specifically targeted regions experiencing a decline in mean Findex scores. This choice of linear regression aligns seamlessly with our research objectives, offering valuable insights into the financial inclusion status of women and low-income adults in the midst of the pandemic (Kumar, 2023).

The selection of linear regression as our analytical method is rooted in its interpretability, alignment with our research objectives, suitability for region-specific analysis, statistical robustness, and compatibility with Principal Component Analysis (PCA) for dimensionality reduction (Mali, 2023). It represents the optimal approach for our project.

Discussion

Region Groups Discussion -

Figure 7 illustrates significant disparities in the FI revolution among Women and Low-Income adults across various regions in 2021, echoing findings by Aslan et al. (2017). Their research emphasised that disparities in economic opportunities, especially Women's access to education and healthcare, contribute to income inequality, further compounded by the growth of the Low-Income Adult population due to socioeconomic factors (McKnight, 2019). Both Women and Low-Income population tend to exhibit lower mean Findex scores compared to the General population, potentially highlighting the byproduct of their financial needs not being met.

Persistent income disparities result from limited access to education, healthcare, and job opportunities stemming from socioeconomic inequalities (Ralli et al., 2021). In such scenarios, a lack of economic mobility and unequal access to essential resources exacerbate income disparities (Dabla-Norris, 2015). Understanding these patterns is critical for identifying nations that have effectively implemented FI practices while addressing gender and economic barriers.

Notably, the SA and SSA regions consistently recorded mean Findex scores below the average FI score of 0.5 in 2021. In the General population, the SA region scored 0.378, and SSA scored slightly higher at 0.416. In the Women population, region SA had a mean Findex score of 0.340, while SSA recorded 0.362. For the Low-Income population, region SA scored 0.352, with SSA slightly lower at 0.320. These regions both fall under a moderate level of FI in 2021 according to the AFI's four-level index categories. This analysis provides insight into country-specific data within these regions, focusing on countries with notably high mean Findex scores, as observed in Figure 7, such as Sri Lanka in the SA region and Namibia, Mauritius, and South Africa in the SSA region.

A World Bank report highlighted Namibia as the third-ranking African nation in FI and the population with bank accounts, followed by Mauritius and South Africa (World Bank, 2016). These countries demonstrated similar FI patterns and account ownership rates. Sri Lanka in the SA region has the highest mean Findex score, showing a high rate of account ownership without a gender gap (FinDev Gateway, 2023). Conversely, Pakistan in the SA region had a considerably lower mean Findex score, attributed to its low account ownership and limited use of financial services (FinDev Gateway, 2023).

These outlier countries' success can be attributed to effective strategies like enhancing banking service accessibility, promoting financial literacy, and establishing supportive regulatory environments. Collaborative efforts involving governments, financial institutions, and stakeholders have fostered the growth of FI by providing access to formal financial services. These countries serve as models for others striving to overcome challenges in their FI development. The knowledge exchange and collaboration among nations not only transcend gender and individual status but also national boundaries.

Region NA exhibited the highest mean Findex scores among all regions. As indicated in the 2021 Global Findex, NA demonstrates remarkable account ownership rates, with 99.6% of Canada's adult population and 95% of United States adults holding financial accounts (FinDev Gateway, 2023). Furthermore, NA's FI strength is reinforced by the widespread adoption of digital financial services. In Canada, 98% of the population reported engaging in digital payments in the past year, while in the United States, this rate remains high at 93%. However, educational disparities within the United States are evident, with individuals of lower education levels being less likely to participate in digital payments. For instance, only 54% of those with primary school education engaged in digital payments, while this figure rises to 94% among those with at least secondary education (FinDev Gateway, 2023). The extensive use of digital financial services has significantly contributed to NA's high Findex scores. Therefore, the adoption of these financial tools plays a pivotal role in enhancing a country's FI index, with education influencing access to these tools.

Income Groups Discussion -

In our analysis, we observed a clear trend of a positive correlation between income group and Findex scores across all of our focus populations. This aligns with the research conducted by Poghosyan (2023), who explored the distribution of FI across four of the same income groups. Poghosyan's study exhibited a pattern that reinforces the notion that higher income levels tend to be associated with improved FI outcomes. The study highlights the dynamics influencing FI, exploring several country-specific factors such as financial development, socio-economic development, institutional quality, and macro-financial stability. As these factors play a pivotal role in shaping FI outcomes, an in-depth understanding of these interdependencies can empower policymakers to craft tailored strategies aimed at increasing FI across multiple countries and economies (Poghosyan, 2023).

Ukraine, Iran, and Mongolia were the 3 outlying countries within the Lower-Middle income group for General and Women populations. The Low-Income Adult population had one matching outlier which was Iran with Saudi Arabia and Sri Lanka being the other two country outliers.

Research done by Murakami (2022) helps in understanding gender disparities in FI, more specifically, with our findings of Mongolia having a higher Findex score that exceeded many other countries within the General and Women populations for the Low-Middle Income group. Murakami (2022) goes on to address that the major determinants of FI for women include their education level and employment status, further explaining that Mongolia has a reversed gender gap in FI of a 4% difference, with more women being financially included than men. It is imperative to note that Mongolia’s reverse gender gap is unlikely to stem from financial systems and policies that discriminate against men as the country scores relatively high in FI for both men and women (Murakami, 2022).

Mongolia stands out as an outlier in the realm of gender disparities in FI due to several unique factors. Contrary to global trends, Mongolian women have better access to formal finance, while men tend to encounter barriers in this regard. This deviation is attributed to cultural factors, where men often engage in traditional herding activities in rural areas, while women pursue education and work in cities (Murakami, 2022).

Educational opportunities have driven women to higher education, contributing to a reverse gender gap in education. Urban-rural disparities in infrastructure development further hinder men's access to formal financial services. Additionally, men's higher participation in the informal sector, often with cash-based wages, adds to this anomaly (Murakami, 2022). The research suggests that addressing educational equality could potentially bridge the gender gap in FI in Mongolia, highlighting one of the many solutions for other countries who experience gender disparities in FI.

Slope Chart Discussion -

Our findings displayed in Figures 4, 5, & 6 highlighted that the ECA region had the most countries that increased in Findex score over the years 2017 to 2021 across all three populations. ECA continues to lead the way in FI, with an increasing number of adults in the region having bank accounts.

The GFD shows the proportion of adults in ECA with bank accounts rose from 65% (2017) to 78% (2021), surpassing the 71% average of the developing economies (FDG, 2023). Along with this, ECA also had the lowest number of inactive accounts compared to other developing economies, with only 3% of adults having inactive accounts, compared to the developing economy average of 13% (FDG, 2023)

ECA is also one of the leading regions in terms of digital payments. ECA adults made or received 74% of digital payments last year, compared to 60% in 2017, making it one of the top regions for digital payments among developing economies. Only EAP has a higher percentage at 76% (FDG, 2023)

Figure 5 shows that Mongolia was the sole country with an increased FI score for the Women population. This finding correlates with prior research, such as Murakami's study, which noted a reversed gender gap in Mongolia, where women tend to have higher financial inclusion compared to men (Murakami, 2022).

It is worth noting that two countries which saw both an increase in the Women and Low-Income adult populations were Peru and Afghanistan. This highlights the interconnectedness of these two demographic groups in the context of FI and suggests that certain initiatives and policies may have benefitted both women and poor adults in these countries. However, it is important to acknowledge that there was no significant research readily available to support the specific findings of increased FI in Peru and Afghanistan. This lack of research could be attributed to several factors, including limited access to comprehensive and up-to-date FI data, potential gaps in research coverage, or challenges in data collection and reporting in these regions. Nevertheless, these findings underscore the importance of conducting further in-depth studies and assessments to better understand the dynamics of FI in Peru and Afghanistan. Such research has the potential to provide valuable insights into the specific policies and interventions that have contributed to improved FI outcomes in these countries.

The analysis of Findex scores within the General population segment reveals some intriguing trends. Notably, B&H stood out with the most significant increase in Findex scores during the period of observation. This indicates a commendable effort in expanding financial access and inclusion within the country. FinDev Gateway (2023) has compared B&H's percent of 'adults aged 15+ that obtain an account at a financial institution or through a mobile money provider' with the World (76%) and ECA region (78%) percentages. B&H scored the highest out of the three (79%) during the year 2021.

FI, reliant on access and use of financial products and services, often falls short for individuals who cannot meet strict banking requirements or afford these services, particularly in lower-income segments (Okičić, 2023). Microfinance offers a range of financial services, including lending and saving, tailored to the needs of those without access to traditional financial products (Okičić, 2023). In Bosnia and Herzegovina, microfinance institutions like MI-BOSPO have successfully adapted their services to clients, particularly women and low-income individuals (Okičić, 2023). MI-BOSPO recognised the challenges their clients faced during the COVID-19 pandemic, leading to the launch of the "Our Classroom" initiative in 2020 and 2021. This initiative aimed to enhance digital financial literacy, improve digital banking skills, address internet safety concerns, and eliminate the need for physical banking visits (Okičić, 2023).

Bosnia and Herzegovina's Findex score for the general population increased due to proactive measures by MI-BOSPO and other financial institutions, which addressed the digital divide, improved financial literacy, and built trust in digital financial services amid the digital transformation (Okičić, 2023). In contrast, the United Arab Emirates and Lebanon witnessed significant drops in their Findex scores, indicating that while some countries, like B&H, improved financial inclusion, others, such as the United Arab Emirates and Lebanon, faced challenges that led to substantial declines (Smith et al., 2022).

The countries with the largest decrease in their Findex scores within each focus population can be largely attributed to the unique financial landscape and challenges within the MENA region. MENA faces distinctive FI hurdles that have a profound impact on Findex scores, resulting in divergent outcomes. First and foremost, MENA is characterised by exceptionally low rates of account ownership, with only 48% of adults in the region having a financial account, significantly lower than the developing economy average. Moreover, the region experiences a notable gender gap in FI, with only 42% of women having financial accounts compared to 54% of men, the highest gender gap among all regions. These factors create a challenging environment for FI initiatives, leading to lower Findex scores (FDG, 2023). In the context of digital payments, the MENA region lags behind other developing economies. The adoption of digital payments is relatively limited, with only 40% of adults reporting digital payment usage, significantly lower than the developing economy average of 57%. This underutilisation of digital financial services can impact the overall FI landscape and contribute to lower Findex scores. Furthermore, the region struggles with financial resilience, as only 21% of adults in MENA can access emergency funding without difficulty, well below the developing economy average of 27%. This lack of financial resilience is compounded by the reliance on informal financial systems, where around half of adults in MENA turn to friends and family for emergency funding. This reliance on informal channels can make it challenging to enhance FI and resilience.

In summary, the challenges associated with low account ownership, a significant gender gap, limited adoption of digital payments, and a reliance on informal financial systems contribute to the substantial decrease in Findex scores in the United Arab Emirates and Lebanon within the MENA region. In contrast, B&H's proactive efforts in digital financial education and FI initiatives have contributed to its positive outcomes, emphasising the region-specific disparities in the global FI landscape.

Narrowing the focus to the Women population, Saudi Arabia leads with the most substantial increase in Findex scores, a notable finding. However, it's important to acknowledge that there is limited concrete research available to solidify this finding, and it appears inconsistent with the broader trends observed in the MENA region in terms of FI. While Saudi Arabia's efforts in improving FI for women are commendable, the unique financial landscape and disparities within the region underscore the need for further research to comprehensively understand and validate the observed trends.

In the case of Low-Income adults, China saw the largest increase in its Findex score, with Brazil following closely behind. China’s progress in the area of FI for this demographic can be attributed to China’s approach which focused on broadening access to and utilisation of financial services for low-income individuals from the years 2015 to date (Ye, 2022). One study looking at the ability of financial technology to reduce poverty in China found that there was a positive impact of fintech on poverty reduction. Ye (2022) found that the effects of fintech on poverty reduction are more pronounced in low-income provinces due to reduced transaction costs, easier access to financial services, providing more accurate information, and reduced risks for households. The studies analysis concluded that a 1% increase in adoption of fintech in high income provinces lead to a 10% drop in poverty, while in low-income provinces it leads to a 20% drop (Ye, 2022).

Within the Low-Income adult population, Brazil also saw a large increase in their Findex scores thanks to the government's response to the pandemic. The government teamed up with the state bank to create a financial support program for self-employed people and informal workers who were affected by the pandemic (Gonzalez, 2023). With more than 84 million adults in Brazil using smartphones, the program introduced a special Android app for low-income people called "Caixa TEM". This easy-to-use, mobile-friendly solution made it easier for people to access financial services, which helps tackle financial illiteracy (Gonzalez, 2023). Not only has Brazil made FI easier for economically vulnerable people, but it's also a great example for other countries to follow when it comes to providing financial services to people in crisis situations.

Fintech has a significant influence on FI, as evidenced by the experiences of China and Brazil. Its contribution to poverty reduction is clear, especially in low-income areas, where even a slight increase in the adoption of fintech can result in substantial reductions in poverty rates. Government initiatives, such as Brazil's response to COVID-19, can be instrumental in broadening FI by providing easy-to-use fintech solutions to economically disadvantaged populations. This provides essential information for future research, which will guide inquiries into the effectiveness of particular fintech interventions and the influence of government policies, as well as the potential for fintech to reduce economic disparities and promote FI.

Bubble Chart & Linear Regression Discussion -

Based on the findings derived from the bubble charts and linear regression analysis, we have observed diverse linear trends in the relationship between Findex scores and the population density of countries across different regions in the year 2021. That is for the Women and Low-Income population, as depicted in Figures 13 and 14.

In our examination of country-specific attributes, we've focused on population density. Alter and Yontcheva (2015) also explored this factor, suggesting that larger, more densely populated countries tend to have more efficient and developed financial services due to a larger customer base. However, our observations in Figures 13 and 14 reveal region-specific findings that differ from Alter and Yontcheva's conclusions. This emphasises the need to consider the proportion of people in different country regions and how it impacts financial service availability, accessibility, and overall financial sector development in a nation.

Regions NA and MENA exhibit results contradictory to Alter and Yontcheva's study (2015), showing a moderate negative correlation between Findex scores and population density. This means that as the population increases, Findex services decrease. MENA's rapid population growth has hampered economic growth due to employment challenges (Eken et al., 1996) and gender disparities in literacy and education (Eken et al., 1996), with only 42% of women having financial accounts compared to 54% of men (FDG, 2023). The literature emphasises the need for effective policy implementation, often with external assistance, to enhance financial inclusiveness.

Álvarez-Gamboa et al. (2021) found that population growth affects economic and social aspects, contributing to multidimensional poverty. A 1% population growth results in an average 4.1% increase in poverty, highlighting the complex link between population density and economic challenges. In NA countries, the expanding population is associated with a moderate and weak trend in financial inclusion, accentuating challenges faced by women and low-income adults in the pandemic year of 2021, such as employment and income inequalities, COVID-19 regulations, and gender disparities, all hindering access to financial services (Butler et al., 2020).

Comprehending the multifaceted factors causing Findex score decline with population growth in NA and MENA is crucial. These insights inform future interventions for inclusivity among women and low-income adults, offering lessons to policymakers and organisations to prevent exclusion among vulnerable populations.

Future Work -

Several promising avenues can expand on our study's findings. Firstly, using choropleth maps can enhance FI data visualisation, providing a geographically intuitive view of regional and income disparities. Secondly, integrating FI data with COVID-19 health outcomes and mitigation plans offers insights into broader socio-economic impacts. Another avenue is conducting a meta-analysis of gender and income gap closure research, offering an overview of current efforts. Lastly, a longitudinal study covering pre-pandemic, pandemic, and post-pandemic periods can delve into FI evolution and the adoption of financial tools, shedding light on changing economic and social landscapes. These research directions promise to improve our understanding of FI dynamics and inform more effective policies and interventions for vulnerable populations.

Constraints -

During our research project, we encountered significant challenges that required innovative solutions. One major issue was the absence of COVID-19 database records for Women and Low-Income populations in 2021. To address this, we shifted our project's focus to gain a broader understanding of 'FI' and assess each nation's FI status in 2021. This allowed us to delve into the social determinants affecting financial service accessibility and their impact on population health, particularly in the absence of COVID-19 data. We also explored the persistent gender gap in account ownership in developing economies, highlighting the challenges faced by Women in adopting FI activities, emphasising the role of governments and policymakers in addressing these disparities.

Another challenge arose during the Exploratory Data Analysis (EDA) phase, where we struggled to define the project's purpose and goals, further complicated by the lack of a COVID-19 database. This phase resulted in a brief delay as we worked to clarify our research objectives, eventually leading to meaningful data visualisation and analysis.

Additionally, during the data processing stage, we identified an unexpected issue related to a variable with near-zero variance for the entire year of 2017, stemming from missing data for Iceland. To maintain the integrity of our analysis, we removed Iceland from our datasets, significantly improving the quality and accuracy of our visualised graphs.

Throughout these challenges, we prioritised transparency and data integrity, underscoring the importance of adaptability and meticulous data management in our research journey.

Limitations -

Recognising the biases and implications in our research project is crucial. Investigating FI among women and low-income adults during the COVID-19 pandemic is valuable, but our study faced limitations. A primary bias was the unavailability of COVID-19 data specific to these populations in 2021. This limitation may have skewed our analysis and restricted our ability to draw precise conclusions about the pandemic's impact on FI for these groups, affecting our understanding of the challenges and vulnerabilities they experienced (Smith et al., 2021).

Conclusion

The extensive analysis and visualisations conducted in this research project have yielded valuable insights into the state of FI for General, Women, and Low-Income adult populations in various countries both before and during the initial year of the COVID-19 pandemic. To ascertain the validity and strength of these findings, it's crucial to evaluate their alignment with our original research goal: "What was the state of FI for women and low-income adults in different countries before and during the first year of the pandemic?"

The findings, which encompass Findex scores and their temporal trends, are directly relevant to our research objectives and questions. Our use of diverse visualisations, such as box plots, scatter plots, slope charts, and linear regression analyses, has significantly improved the accessibility of complex data, making it easier to discern patterns and identify outliers. Moreover, our region-specific and income group analyses have provided a nuanced understanding of FI dynamics.

In summary, our research has successfully delivered on its core objective, shedding light on the state of FI for women and low-income adults during the first year of the pandemic and enhancing our understanding of these dynamics through a variety of data visualisations and analyses.

We are confident that the results of our project will provide useful information for international policy-makers, financial institutions, and researchers to further explore this subject and the next steps that are necessary to create environments that are financially equitable for all, but above all, for those who are most in need.

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Appendices

Figure 1. Correlation between Mean Findex of the General Population and Regional Classification, 2017 & 2021

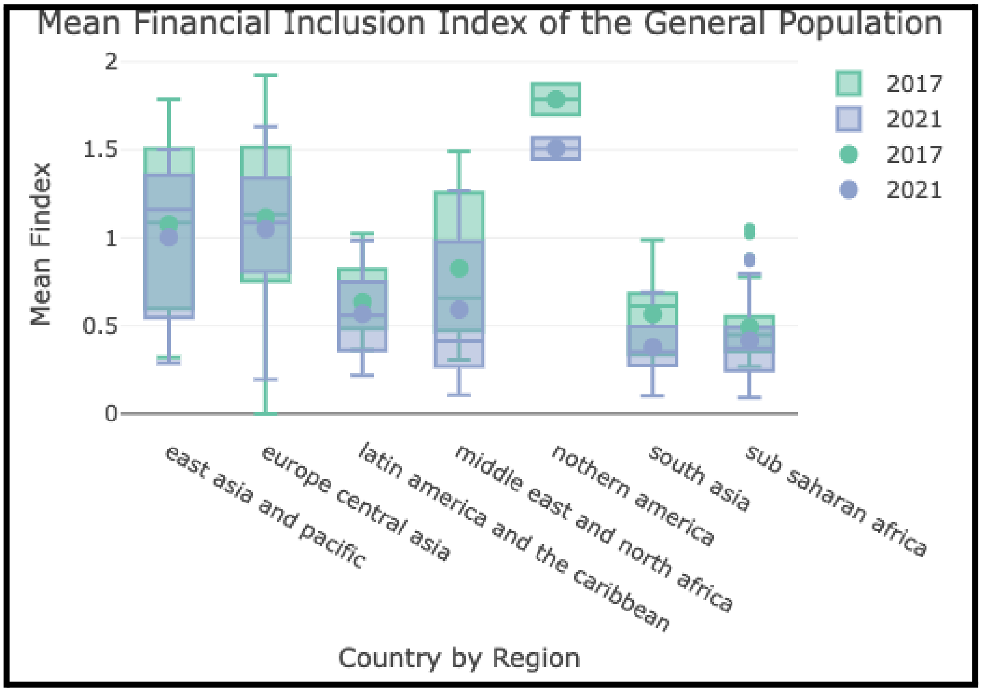

Figure 2. Correlation between Mean Findex of the Women Population and Regional Classification, 2017 & 2021

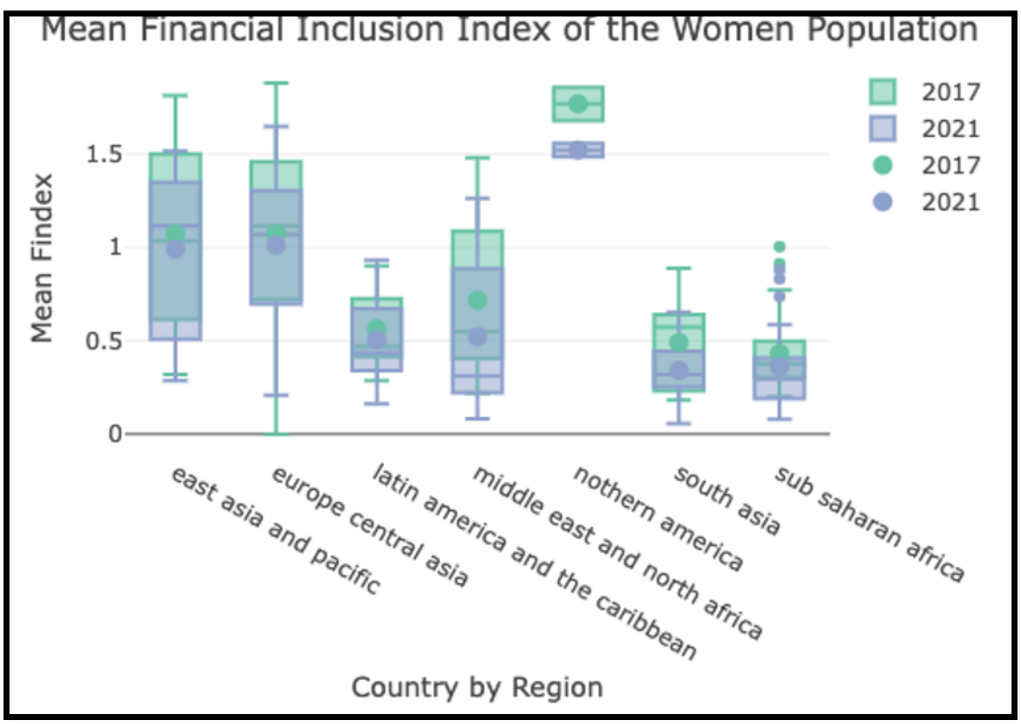

Figure 3. Correlation between Mean Findex of the Low-Income Adult Population and Regional Classification, 2017 & 2021

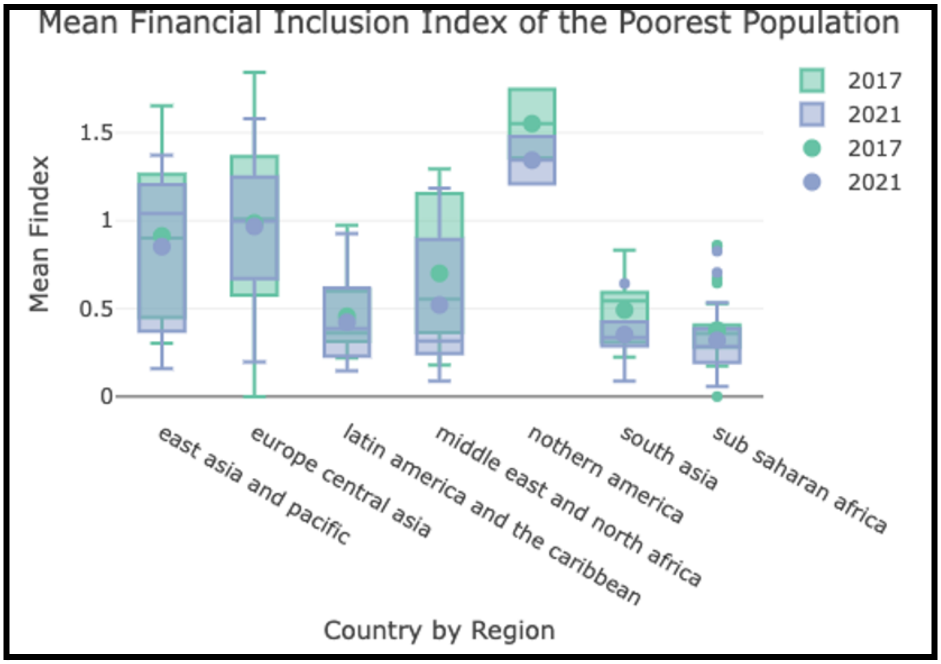

Figure 9: Correlation between Findex scores of countries and General Population Density per region in 2021

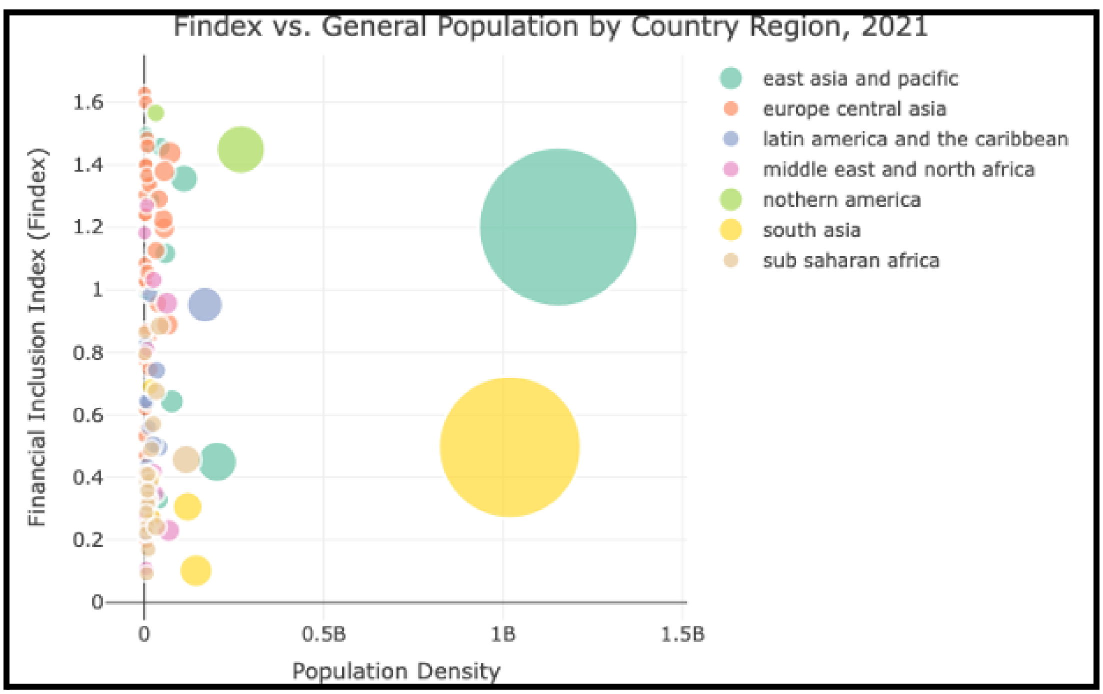

Figure 10: Correlation between Findex scores of countries and Women Population Density per Region in 2021.

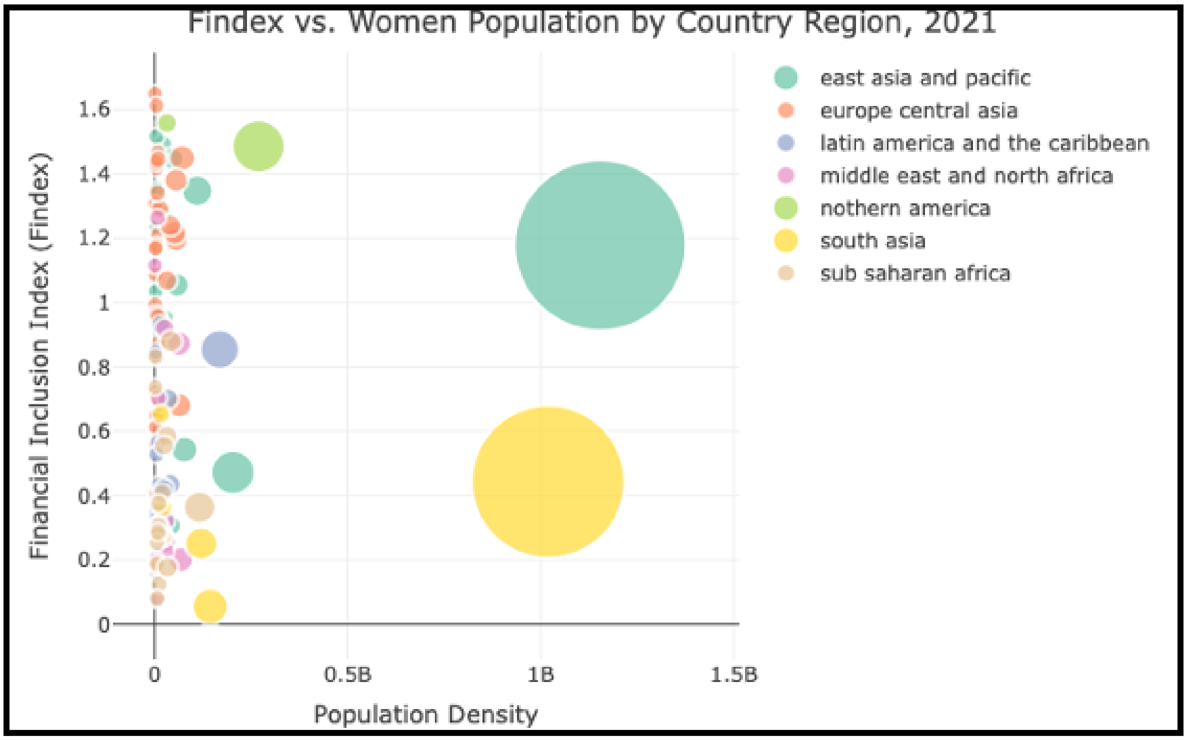

Figure 11: Correlation between Findex scores of countries and Low-Income Population Density per Region in 2021.

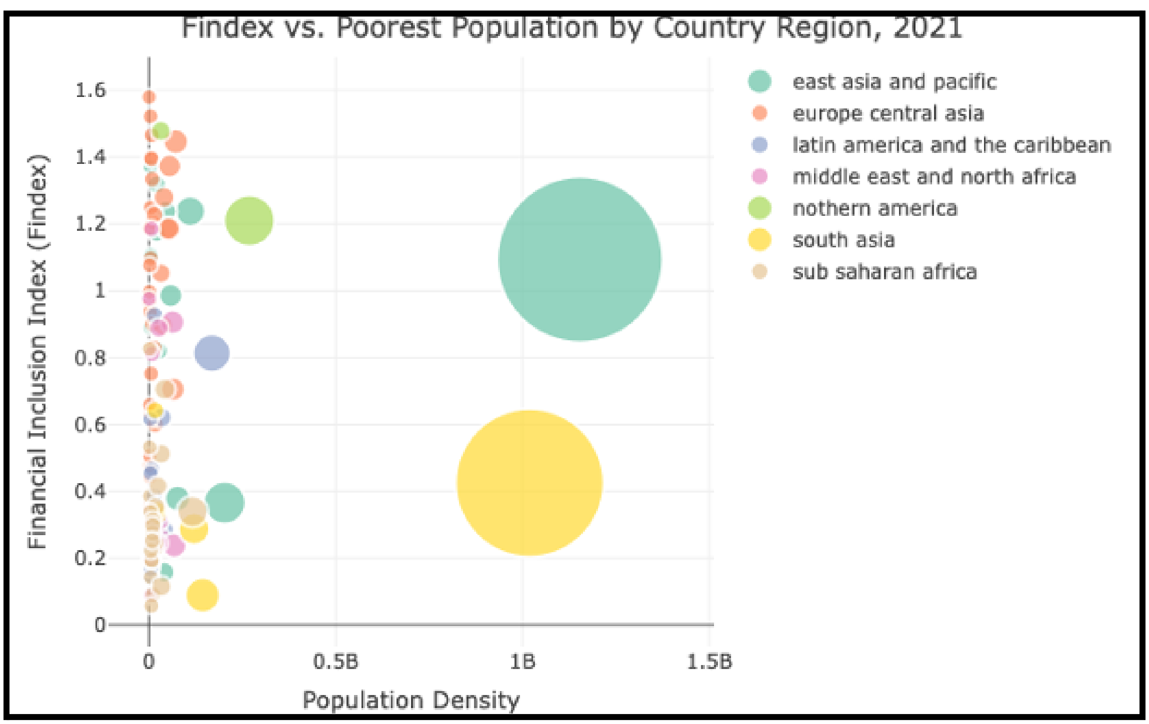

Figure 16: Bar Chart showing Countries that saw an increase in their Findex score from 2017 to 2021 for all focus populations

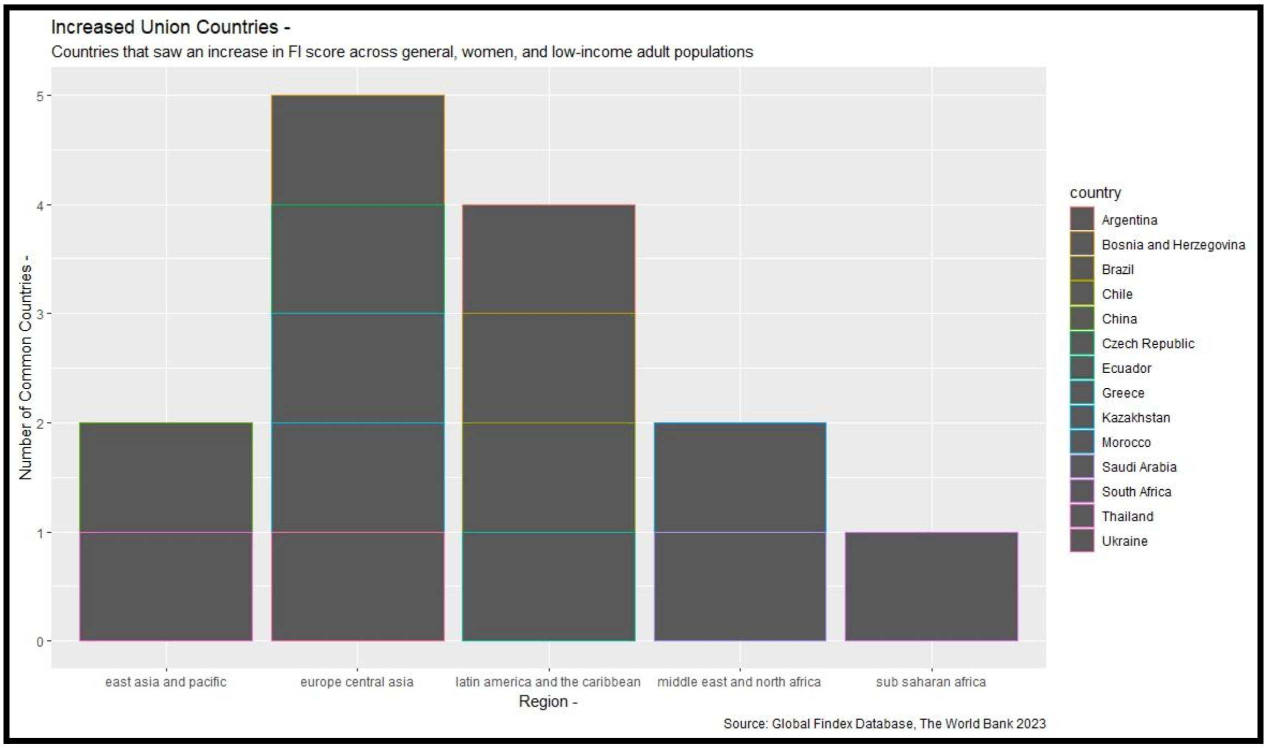

Figure 17: Bar Chart showing Countries that saw a decrease in their Findex score from 2017 to 2021 for all focus populations (will have to zoom in to view clearly)

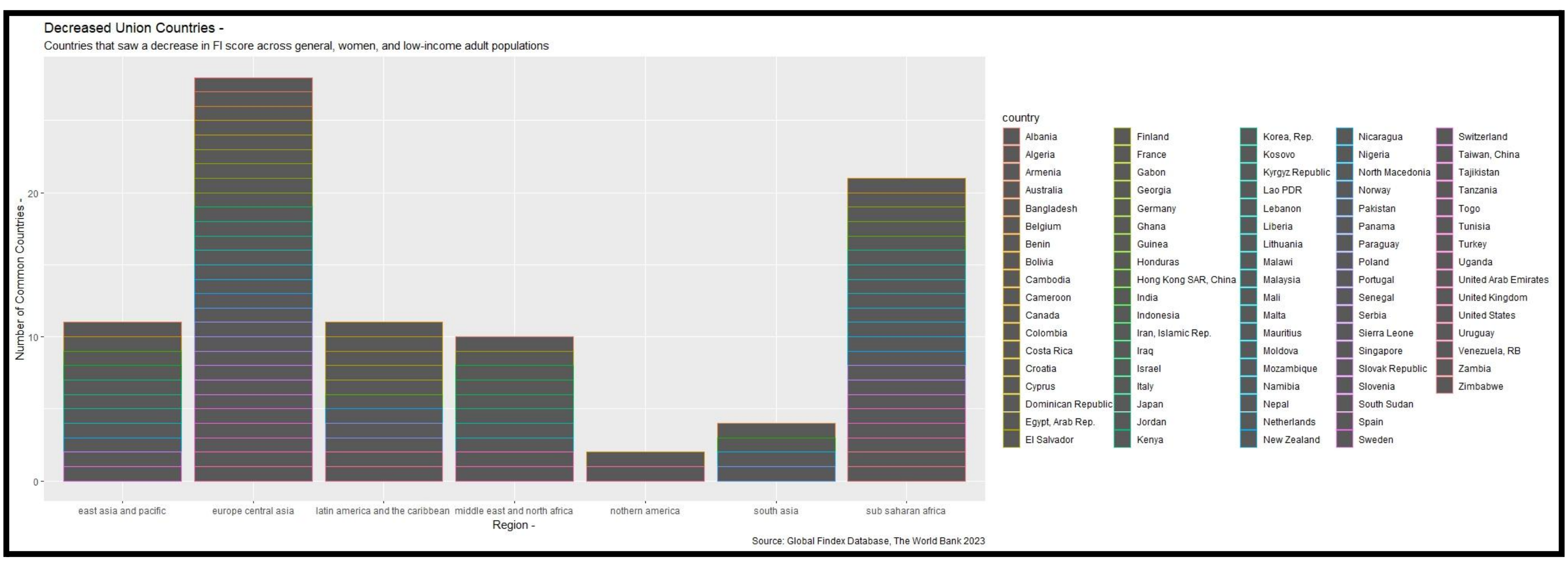

Figure 18: Boxplot showing General Population Findex Scores by Income Group between the years 2017 & 2021

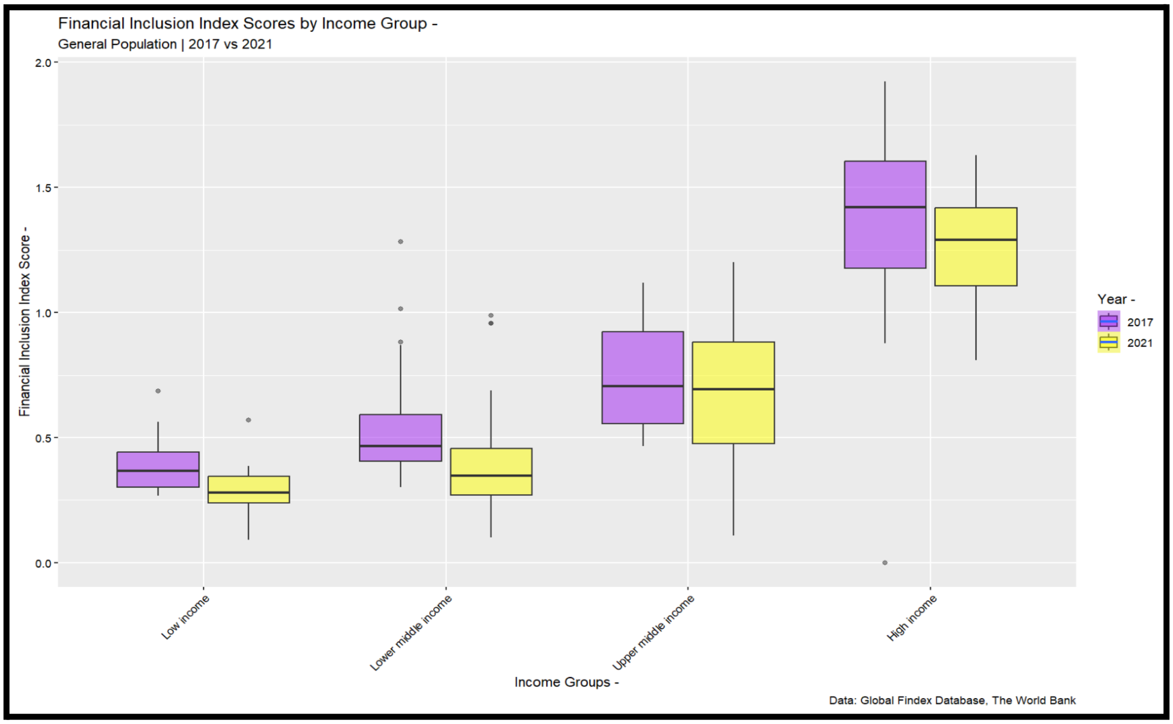

Figure 19: Boxplot showing Women Population Findex Scores by Income Group between the years 2017 & 2021

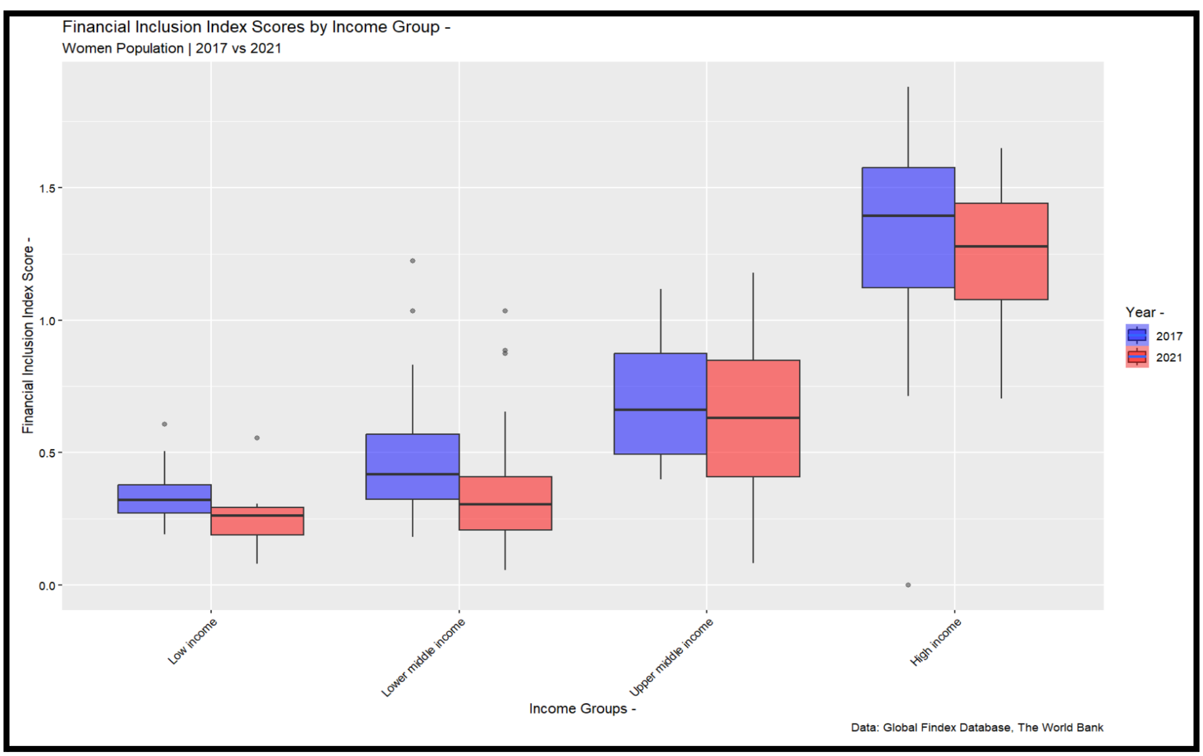

Figure 20: Boxplot showing Low-Income Adult Population Findex Scores by Income Group between the years 2017 & 2021

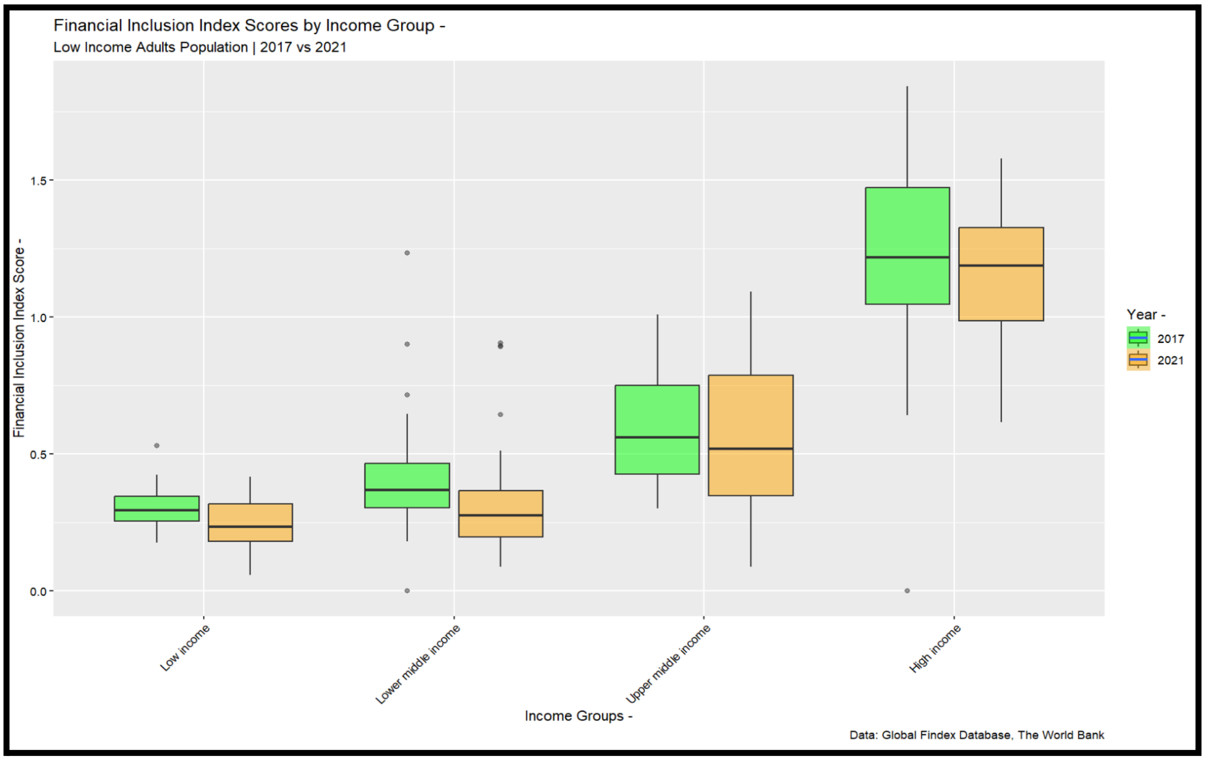

Table 2. Mean FI Index (Findex) Across All Focus Population Groups (3s.f)

Region	General											
	Mean Findex											
	2017						2021					
	Min	Q1	Median	Mean	Q3	Max	Min	Q1	Median	Mean	Q3	Max
East Asia and Pacific	0.320	0.599	1.086	1.076	1.506	1.788	0.290	0.546	1.159	1.002	1.356	1.500
Europe Central Asia	0.000	0.756	1.133	1.114	1.514	1.923	0.195	0.807	1.086	1.049	1.339	1.630
Latin America and the Caribbean	0.365	0.483	0.557	0.635	0.821	1.022	0.219	0.361	0.560	0.568	0.751	0.984
Middle East and North Africa	0.305	0.471	0.656	0.825	1.256	1.490	0.108	0.270	0.411	0.591	0.976	1.270
Northern America	NA	1.699	1.787	1.787	1.877	NA	NA	1.450	1.510	1.508	1.566	NA
South Asia	0.274	0.334	0.614	0.566	0.685	0.988	0.101	0.273	0.352	0.378	0.497	0.690
Sub-Saharan Africa	0.269	0.354	0.449	0.492	0.775	1.054	0.092	0.244	0.371	0.416	0.490	0.884
	Women											
	Mean Findex											
	2017						2021					
	Min	Q1	Median	Mean	Q3	Max	Min	Q1	Median	Mean	Q3	Max
East Asia and Pacific	0.320	0.614	1.035	1.072	1.501	1.814	0.286	0.508	1.117	0.991	1.350	1.517
Europe Central Asia	0.000	0.721	1.116	1.071	1.459	1.880	0.209	0.670	1.069	1.013	1.304	1.649
Latin America and the Caribbean	0.286	0.414	0.468	0.564	0.725	0.901	0.161	0.339	0.435	0.505	0.672	0.932
Middle East and North Africa	0.220	0.406	0.549	0.717	1.086	1.480	0.825	0.223	0.312	0.522	0.885	1.264
Northern America	NA	1.680	1.770	1.770	1.859	NA	NA	1.486	1.522	1.522	1.558	NA
South Asia	0.182	0.231	0.574	0.490	0.640	0.888	0.056	0.252	0.318	0.340	0.443	0.653
Sub-Saharan Africa	0.201	0.305	0.376	0.432	0.772	1.004	0.079	0.189	0.293	0.362	0.407	0.880
	Low-Income Adults											
	Mean Findex											
	2017						2021					
	Min	Q1	Median	Mean	Q3	Max	Min	Q1	Median	Mean	Q3	Max
East Asia and Pacific	0.303	0.451	0.901	0.914	1.263	1.652	0.157	0.372	1.040	0.851	1.205	1.371
Europe Central Asia	0.000	0.577	1.010	0.987	1.364	1.843	0.197	0.670	0.997	0.967	1.248	1.580
Latin America and the Caribbean	0.218	0.312	0.362	0.456	0.601	0.974	0.145	0.229	0.385	0.422	0.617	0.926
Middle East and North Africa	0.180	0.364	0.554	0.701	1.153	1.295	0.088	0.244	0.317	0.521	0.893	1.185
Northern America	NA	1.358	1.552	1.552	1.746	NA	NA	1.210	1.344	1.344	1.478	NA
South Asia	0.224	0.309	0.543	0.492	0.593	0.833	0.089	0.288	0.335	0.352	0.425	0.643
Sub-Saharan Africa	0.000	0.279	0.360	0.378	0.407	0.860	0.057	0.194	0.286	0.320	0.385	0.827