A multi-dimensional index of financial inclusion: a micro-data approach

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Summary

Financial inclusion (FI) has become a buzzword in development studies. However, few studies have quantified FI using multi-dimensional approaches and the majority select macroeconomic variables. Therefore, this article constructs an index of FI using the World Bank's Findex, a dataset with micro-data for about 150 countries over three years. As variables are binary, the selected method is multiple correspondence analysis. This novel measurement allows for a more precise analysis of the relationship between FI and other factors. To illustrate that, this article estimates the determinants of FI based on individual's characteristics. It also proposes a new ranking for countries.

Key words – multidimensional measurement, financial inclusion, multiple correspondence analysis, index

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1. Introduction

Financial inclusion (FI) has been widely discussed among academics and policy makers in the development community, in particular after evidence of nil or harmful effect of microfinance has been presented (Banerjee, Karlan, & Zinman, 2015; Duvendack et al., 2011; van Rooyen, Stewart, & de Wet, 2012). Defined here as the access and usage of credit, deposit, savings, payments and insurance by individuals provided through for-profit financial institutions, current studies quantify FI either through a one-dimensional aspect or from a macroeconomic approach.

In order to assess the determinants of FI, existing studies make use of an extensive survey on FI organised by the World Bank called the Findex (Allen, Demirguc-Kunt, Klapper, & Martinez Peria, 2016; Fungáčová & Weill, 2015; Wang & Guan, 2017; Zins & Weill, 2016). Since the database is constituted of mostly categorical data, these studies perform econometric analysis using only a single dimension each time, such as account ownership or formal credit. However, the multi-dimensional characteristics of FI is left aside due to data constraints.

Similarly, another stream of the literature prefers to use macroeconomic variables, such as number of ATMs per 1,000 adults or credit per GDP ratio, in order to create a multi-dimensional measurement of FI by using standard index creation techniques, including principal component analysis (PCA) or factor analysis (Amidžić, Massara, & Mialou, 2014; Chakravarty & Pal, 2013; Honohan, 2008; Piñeyro, 2013; Sarma, 2016).[1]

Meanwhile, two further studies attempt to integrate a multi-dimensional approach to the usage of the Findex dataset, but the outcomes are problematic. Camara & Tuesta (2014) use PCA for analysing binary variables and incorporate it to the macroeconomic measurement, thus yielding results very similar to the standard macroeconomic indexes. Aslan, Deléchat, Newiak, & Yang (2017), on the other hand, use joint correspondence analysis (JCA) in order to reduce the data but, by choosing different variables for each year, besides not handling missing values, the outcome is hard to be compared overtime.

This paper overcomes the issue of creating an index for FI selecting solely categorical variables by using MCA to reduce the dimensions of eleven variables stemming from the Findex database. By providing a multi-dimensional index, we are able to assess the determinants of FI based on individual characteristics for around 150,000 individuals from developed and developing countries over time, besides creating a country ranking of the most financially included countries in the world.

The paper is structured as follows: Section 2 introduces the dataset, while Section 3 elaborates on the method used in order to construct the FI index. Section 4 applies the index in order to assess the determinants of FI using individual's characteristics. Section 5 creates the global ranking of FI. Last section concludes.

2. Data

The Global Findex database has been launched in 2011 by the World Bank, with funding from the Bill and Melinda Gates Foundation, and further survey rounds were conducted in 2014 and 2017 (Demirguc-Kunt, Klapper, Singer, Ansar, & Hess, 2018). Using nationally representative

[1] Further details on selected variables and methods in Appendix.

data[2] for 149,761, 146,688 and 154,923 individuals, respectively, the survey is constituted of categorical variables that include questions on account and credit card ownership, formal savings and formal credit, as well as different purposes of credit usage. Moreover, the dataset provides information on individual's characteristics, including gender, age, income quintile and educational level.

While some countries have been dropped or added in each wave, all of them include high income, upper and lower-middle income countries as well as low-income countries. Most countries have a sample of around 1,000 individuals per year, but larger countries such as China have a sample size of around 4,000 individuals. Likewise, smaller countries such as Haiti has a sample size of around 500 individuals.

Survey coverage represents more than 97% of the world's population. Where telephone coverage represented less than 80% of the population, face-to-face interviews were conducted. For the former, random digit dialling or a nationally representative list of numbers were used. For the later, sample was randomly selected within the household using the Kish grid method.[3]

Among the 18, 44 and 48 questions for 2011, 2014 and 2017 respectively, we selected the main 11 indicators that fit the access, credit and savings dimensions.[4] Unfortunately, insurance was only surveyed in 2011, reason why we decide to leave this dimension out of the index. Furthermore, questions on frequency of deposits and withdrawals, as well as payment, were also left out, as those corresponded only to those with an account at a financial institution, thus causing the data not to vary. Table 1 presents the selected variables for the index construction and their respective dimensions. These indicators are binary variables that take the value of 1 if yes and 0 if no.

Table 1. *Selected variables for the novel financial inclusion index*

Dimension	Variable
Access	Account at a financial institution[5]
	Debit card ownership
	Credit card ownership
	Mobile money account[6]
Credit	Loan from financial institution in past 12 months
	Loan from a store (store credit) in past 12 months[7]
	Loan to start, operate, or expand a farm or business in past 12 months[8]
	Loan for school fees[9]
	Loan for health purposes
	Loan for home purchase
Savings	Savings at a financial institution in the past 12 months

[2] Weights are based on household size, sex, age, education and socioeconomic status and are provided by the Findex dataset (Demirgüç-Kunt & Klapper, 2013)

[3] Further information on data collection can be found at www.worldbank.org/globalfindex

[4] Description of indicators can be found in the appendix.

[5] For 2011, there are three variables for account ownership: q1a, q1b and q1, and the latter is a composite indicator. This indicator, however, suffers of several drawbacks, which are explained in the appendix.

[6] For 2011, a new variable was created in order to be comparable to the ones of 2014 and 2017. Further information in the appendix.

[7] Not available for 2017.

[8] Not available for 2011.

[9] Not available for 2017.

3. Method

(a) *Multiple correspondence analysis*

As in Akotey & Adjasi (2016), Booysen, van der Berg, Burger, Maltitz, & Rand (2008) and Pasha (2017), I select the most appropriate method to construct an index using only binary variables. Multiple correspondence analysis (MCA), for imposing fewer constraints on data, is more suitable for the analysis of discrete or categorical variables than principal correspondence analysis (PCA), by far the most common technique for constructing indices.

According to Husson & Josse (2014), the first step in MCA is to recode the data, usually using the indicator matrix of dummy variables. An indicator matrix is a table that links individuals and categories. Its elements will be 1 where the category was chosen and 0 otherwise. It is also described as a matrix of dummy variables (Greenacre & Blasius, 2006).

Data-driven weights can be particularly advantageous in comparison to other techniques, such as the counting approach, in which normative weights are designated (Pasha, 2017). In the case of equal weights, this particular technique suffers from "perfect substitutability", which means that an increase/decrease in one variable can be equally offset by a decrease/increase in another one, as they will have equivalent values (Sarma, 2016). Likewise, arbitrary weights hold a judgement value that may be considered reasonable or not (Decancq & Lugo, 2013).

Unlike PCA, which uses an orthogonalisation technique, MCA assigns scale values to each of the categories of a variable and maximises the variance of those scores, transforming the association between categories and displaying them in a multidimensional space (Dungey, Doko Tchatoka, & Yanotti, 2018).

In the visual representation, the principal inertia (eigenvalues), similarly to PCA, is used as a criterion for retaining the axes that will be analysed. In MCA, two approaches can be used. First, according to the Kaiser-criterion, axes should be selected so 80% of the variance will be "explained". Another criteria is to select axes, where the explained percentage is larger than $100/(p-1)$, and p is the lowest number of columns or rows (Hjellbrekke, 2018).

The assigned weights and coordinates in the plots will then be useful to generate the scores for each individual, as we see next.

(b) *Index construction*

MCA is useful not only for the geometrical representation it yields, but also for its capacity of generating scores based on the standardisation to either rows or columns coordinates (Blasius & Greenacre, 2014). Standard row scores are computed as the row coordinate R for the tth dimension for the ith observation with indicator matrix elements Z_{ih}:

$$R_{it} = \sum_{h=1}^{J} \frac{Z_{ih}A_{ht}}{q\sqrt{\phi_t}} \tag{1}$$

"where A is the matrix of standard coordinates, q is the number of active variables in the analysis, and ϕ_t is an eigenvalue of the CA on the Burt matrix" (Stata, 2013). However, as we are using principal normalization, we multiply the row score by the square root of the corresponding principal inertia (eigenvalue), so that

$$R_{it} = \sum_{h=1}^{J} \left(\frac{Z_{ih} A_{ht}}{q \sqrt{\phi_t}} \right) \sqrt{\phi_t} \quad (2)$$

As previously explained, there are two criteria to decide on which axes to retain. In this analysis, the first dimension explains the variance of 72.9% in the dataset and the second dimension, 10.1%, which suffices to represent more than 80% of the explained variance. Moreover, as there are eleven variables, which yields eleven columns, the retained axes are above the 10% threshold. Therefore, for the visual representation there is the inclusion of only the first two axes.

However, after retaining the first two dimensions, we face an issue with the plot. As the software is not able to programme which of the binary answers are positive or negative, the coordinates are displayed as “no” being a positive value and “yes” as a negative one. This is troublesome as in our interpretation those individuals with more affirmative answers are the most financially included. To solve this, we can pre-multiply the matrix of principal coordinates by -1, which will invert the position of the coordinates, thus giving us an easier interpretation of the plot and scores. This pre-multiplication is also necessary for the score generation.

For the index, as we find that the strong first dimension is a good indicator of FI, so we decide on selecting only this dimension to generate the scores. After yielding the row profiles, we pre-multiply by the category-weights of this first axis.[10]

After weighting it according to the individual’s national representation, we reach a single value to each individual in the sample, for each of the three available years. The results are then normalised with values between 0 and 1 and multiplied by 100 for a less complicated interpretation. Quantifying FI allows us then to estimate the effect of these determinants, analysing the differences among individuals and comparing the results to the graphical representations of MCA. It also gives us the dimension of these differences, unlike in existing probit estimations.

In order to better grasp the index construction, we show the values of particular individuals in the dataset. Table 2 illustrates key values of our index by presenting the answers of individuals, their respective weights and the index values. For instance, our lowest value is from a 28-year-old Japanese woman belonging to the poorest 20% of the income distribution. Her educational level is missing. While several indicators are missing, her negative responses to two of the questions, besides the high allocate weight make her index value to be the lowest in our sample. In contrast, our highest value is from a 29-year-old Austrian man who is part of the middle 20% of the income distribution with a secondary educational level. Again, some answers are missing, but the positive answer to most of the questions, besides the high nationally representative weight given, transforms his index value into the highest in our sample.

[10] More on Figure 1 in the following sub-section.

Table 2. *Composition of particular values of the financial inclusion index*

Closest to	Index value	Negated MCA score	Weight[11]	Year	Country	Indicator										
						Formal account	Debit Card	Credit Card	Mobile money	Formal loan	Store credit	Loan business	Loan school	Loan health	Loan housing	Formal savings
Lowest value	-1.136	- 0.325	3.502	2014	Japan	No	.	.	No	.	.	.	.	.	.	.
25%	-0.123	- 0.125	0.988	2011	Guinea	No	No	No	No	No	No	.	No	No	No	No
Median	-0.000	-0.000	1.133	2011	Russia	No	Yes	No	No	No	No	.	No	No	No	No
Mean	0.018	0.060	0.299	2017	Philippines	Yes	No	No	No	Yes	.	Yes	.	No	No	No
75%	0.116	0.270	0.429	2017	Panama	Yes	Yes	No	No	Yes	.	No	.	No	Yes	No
Highest value	4.039	0.847	4.763	2011	Austria	Yes	Yes	Yes	.	.	Yes	.	.	.	Yes	Yes

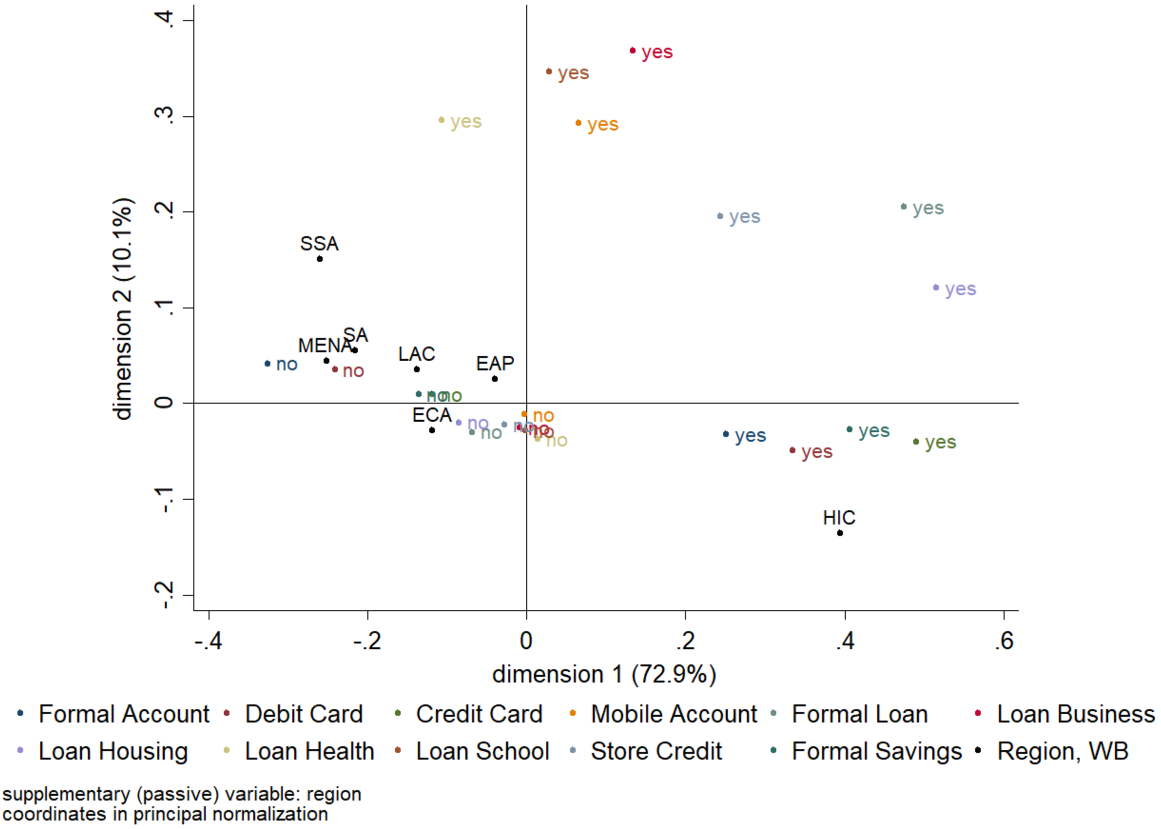
Note: Some of the variables are missing due to lack of information, while others are missing as individuals have refused to answer the question.

[11] Nationally representative weight provided by the World Bank's Findex dataset.

(c) *Analysis*

A first look into our data shows that there seems to be striking differences between regions with respect to FI. Moreover, certain financial services seem to be more related to some than to others, as we see in Figure 1.

Figure 1. *Financial inclusion by region (pooled version)*[12]



Using the Euclidean space, MCA allows us to project the answers of 446,776 individuals from the 2011, 2014 and 2017 surveys.[13] The horizontal axis (dimension 1) is related to FI variables. The more to the right, the more financially included an individual is. The vertical axis shows the indebtedness characteristic of individuals. Those in the upper quadrants are more indebted.

The interpretation of the active variables[14] in the plot is straightforward: answers are clustered together if individuals say yes/no to them concomitantly. Moreover, frequent answers are placed close to the origin (mean) and rare answers far from the origin.

Bearing it in mind, we notice that basic financial services (formal account, debit card, credit card and formal savings) are clustered together in the down-right quadrant. This means that, in our sample, several individuals make use of these services simultaneously. More advanced

[12] The abbreviations correspond to World Banks' regions: High Income Countries (HIC), East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and Caribbean (LAC), South Asia (SA), Middle East and North Africa (MENA), and Sub-Saharan Africa (SSA).

[13] In order to establish a comparison to the index values, the x-axis of this plot was negated, which means this is a mirror version of the automatically generated plot.

[14] Active variables are those used to construct the axis and the index, i.e., the 11 financial inclusion indicators.

services, such as store credit, formal loan and loan for housing are scarce and find themselves far from the origin. Likewise, mobile money accounts as well as loan for business, health care and school fees are less predominant and appear at the top of the plot.

By adding world regions as supplementary variables[15], we are also able to see where particular world regions are placed based on the information given by its population. High income countries (HIC) seem to have individuals who are mostly included and less indebted. On the other end, Sub-Saharan African (SSA) countries seem to be less included and more indebted. Similarly, the Middle East and North Africa (MENA) region appear to be as excluded as SSA, but presents lower levels of indebtedness.

In sum, we notice that low and middle-income countries seem to be more excluded than high income ones, which has been noted in the existing literature (Demirguc-Kunt et al., 2018; World Bank, 2014). However, a more precise analysis can be delivered by assessing these differences through statistical analysis.

4. Determinants of financial inclusion

Using MCA allows us to have a more robust assessment of the determinants of FI. Using the generated index value of each observation as the dependent variable, we can econometrically test the effect of individual's characteristics on FI to understand more in depth who are the financially included. As the sample in our analysis has been randomly selected for each of the three years, we use an independently[16] pooled cross section over time. We estimate the following equation:

$$FI_{it} = \beta_0 + \beta_1 female_{it} + \beta_2 educ_{it} + \beta_3 inc_{q_{it}} + \beta_4 age_{it} + \beta_5 age_{it}^2 + \beta_6 HIC_{it} + \beta_7 year_{it} + \varepsilon_{it} \qquad (3)$$

Exogenous variables are related to individual characteristics. *female* is a dummy variable with the value of 0 when male and 1 when female. *age* is a continuous variable that represents the individual's age and *age2*, its squared value. *educ* is a categorical variable and represents the highest level of educational level of the individual: primary or less, secondary and tertiary or more. *inc_q* is the income quintile in which individuals find themselves. It can be the poorest 20%, second 20%, middle 20%, fourth 20% or richest 20%.

educ and *inc_q* could have endogeneity problems as, according to the mainstream theory, financially included individuals would be able to afford education, thus having better employment opportunities and increase their income. While an instrumental variable analysis is not possible due to lack of instruments in the dataset, an estimation excluding these variables has showed that these do not bias the results for other coefficients. So, if there is endogeneity, the issue is not severe. Lastly, we have dummy variables for years, in order to assess if there has been a difference over time.

In order to test if developed and developing countries' individuals follow the same regression function, we can also perform a Chow test. The result for the test was of 2764.5583, which is

[15] Also known as "passive" variables, supplementary variables yield additional points to the row or column profiles that have zero mass, so not influencing the result of the active variables (Greenacre & Blasius, 2006).
[16] "Since distributions of variables tend to change over time, the identical distribution assumption is not usually valid, but the independence assumption is. This approach gives rise to independent, not identically distributed observations" (Wooldridge 2002, p.128).

statistically significant at the 1% level (the critical value of the F-distribution is 4.6052177). This provides us with information that there are differences between individuals in these two regions, which had been already acknowledged in the visual representation using the MCA analysis. We implement then the variable *HIC*, which assumes the value of 1 when the individual's country is a high income country (denomination made by the World Bank and might change over time) and 0 when the country is a middle or low-income country. This controls for differences between developed and developing countries.

Lastly, a White test is used to test errors for heteroskedasticity. We reject the null hypothesis that the residuals are homoscedastic, reason why we correct for this problem by using robust standard errors.

We first estimate the above equation for 446,776 individuals, including the HIC variable. The result shows that being from a HIC increases FI by 5.90% with a statistical significance at the 1% level and a R^2 of 0.66. This corroborates our Chow test that shows that there are differences between developed and developing countries. Thus, we decide to estimate FI for each of the two different groups, as we see in Table 3 and Table 4.

Table 3. *Determinants of financial inclusion in developed countries (HIC=1)*

Variable	Coef.	Rob. Std. Err.
female	-1.25***	0.041
educ		
secondary	2.10***	0.075
completed tertiary or more	1.90***	0.079
inc_q		
second 20%	0.66***	0.075
middle 20%	0.95***	0.073
fourth 20%	0.97***	0.070
richest 20%	0.57***	0.067
age	0.40***	0.006
age2	-0.00***	0.000
year		
2014	16.32***	0.051
2017	14.77***	0.054
cons	14.83***	0.165

R^2 :0.52

Obs: 128,249

P>F: 0.000

Table 4. *Determinants of financial inclusion in developing countries (HIC=0)*

Variable	Coef.	Rob. Std. Err.
female	-0.30***	0.019
educ		
secondary	2.47***	0.021
completed tertiary or more	4.36***	0.033
inc_q		
second 20%	0.56***	0.033
middle 20%	1.08***	0.032
fourth 20%	1.67***	0.032
richest 20%	2.34***	0.030
age	0.26***	0.003
age2	-0.00***	0.000
year		
2014	16.98***	0.020
2017	14.09***	0.022
cons	8.87***	0.062

R^2:0.68

Obs: 318,527

P>F: 0.000

Despite being consistent with different one-dimensional studies that show that women have a lower likelihood in accessing and using financial services (Allen et al., 2016; Anzoategui, Demirgüç-Kunt, & Martínez Pería, 2014; Ehrmann & Ampudia, 2017; Fungáčová & Weill, 2015; Zins & Weill, 2016), the estimation shows that the gender effect is almost nil. At the same time, a puzzling result emerged: while displaying a small effect, being a woman in developed countries reduces FI by more than in developing countries.

Furthermore, in developed countries education and income levels have less impact on the FI of individuals. Using primary education as a reference value, having secondary or tertiary education increases FI by only 2.1p.p. and 1.9p.p., respectively. Similarly, being richer also affects little the level of FI: in comparison to the bottom 20% of the distribution, other income quintiles increase FI by less than 1p.p.

In developing countries, nonetheless, education and income have a greater impact on the level of FI. Having tertiary or further education increases FI by 4.36p.p. in comparison to primary education or less. Furthermore, being on the top of the income distribution increases FI by 2.34p.p. in comparison to the bottom 20%.

Lastly, we see that being part of the 2014 and 2017 surveys increased FI by about 16 p.p. and 14 p.p., respectively. While this suggests that FI policies have been successful throughout the years in both developed and developing countries, this conclusion must be taken carefully. While similar, the different weights given in each year reduce the possibility of a precise over time comparison.

5. Global Ranking of Financial Inclusion

A common method of comparing the level of FI worldwide has been through country ranking (Amidžić et al., 2014; Camara & Tuesta, 2014; Honohan, 2008; Sarma, 2016). However, existing indexes have been constructed using macroeconomic variables, such as domestic credit provided by financial sector as a share of GDP, number of commercial bank branches per 100,000 adults or number of automated teller machines (ATMs) per 1,000 square kilometres.

While aggregated information can be useful for a cross-country and over time comparison, it can also illustrate an incomplete picture of FI.[17] The use of number of ATMs and bank branches per 100,000 adults (or per 1,000 km^2) is one example of potential biased results. As several countries have digitalised in the past years, there has been a reduction of this type of physical presence in highly financially included countries, as highlighted by Sarma (2016). According to Demirguc-Kunt et al. (2018), 29% of adults used the internet to pay bills or buy something online worldwide in 2017 – ranging from 68% in HICs to 11% in developing countries excluding China. Thus, the need for bank branches or ATMs might have diminished and using it as a measure for FI could bias the index results, in particular for developed countries.

The volume of credit as a share of GDP and other national-level financial development measurements are also deceptive as credit can be concentrated on large firms, and not on individual loans. Demirguc-Kunt and Klapper (2013, p.290) use data from 2011 to compare Vietnam and Czech Republic in order to illustrate this issue. In Vietnam, the amount of domestic credit to the private sector corresponds to 112% of GDP, while only 21% of individuals have a formal bank account. In contrast, Czech domestic credit to the private sector is 55% of GDP, but 81% of adults have a bank account. Hence, aggregated data can end up providing an inaccurate view of finance, both in developed and developing countries.

Therefore, an index using micro-data can be more accurate in providing information on FI at the individual level. In order to elaborate the ranking, we use the index value and calculate the simple average on all the individuals of the respective country. This will yield a single value for each country, which is used for the cross-country ranking (Table 5). It is important to notice, nonetheless, that the scores for developed countries are somewhat overestimated for 2011, as debt and mobile phone usage variables were not part of the survey for this group.[18]

[17] A more detailed discussion about the difference between demand and supply-side data of financial inclusion can be found in Klapper and Singer (2017).
[18] Full list in Appendix.

Table 5. *The Global Ranking of Financial Inclusion (GRFI)*[19]

Rank	GRFI 2011	Score value	GRFI 2014	Score value	GRFI 2017	Score value
1	Sweden	1	Norway	1	Norway	1
2	New Zealand	0.96096832	New Zealand	0.94831634	Canada	0.93925679
3	Finland	0.94250089	Canada	0.93279457	New Zealand	0.88149965
4	Australia	0.9352718	Sweden	0.92034501	Sweden	0.88137692
5	Canada	0.91992617	Finland	0.88955343	Luxembourg	0.8646971
6	Denmark	0.90344626	Australia	0.86555076	Finland	0.84391421
7	Netherlands	0.87696278	United Kingdom	0.85406357	Australia	0.84148878
8	Luxembourg	0.87541926	Luxembourg	0.84831798	Denmark	0.82942843
9	United States	0.82916677	Denmark	0.83552569	United States	0.82450575
10	Belgium	0.81719321	Israel	0.81867319	United Kingdom	0.81950557
…						
50	China	0.38146341	Macedonia, FYR	0.44174486	Chile	0.44856235
51	Brazil	0.36063302	Saudi Arabia	0.4406527	Bulgaria	0.43778038
52	Saudi Arabia	0.36016682	Greece	0.44059163	Hungary	0.4362646
53	Serbia	0.35669553	Jamaica	0.43168354	Venezuela, RB	0.42537856
54	South Africa	0.35139075	Serbia	0.43029857	Uruguay	0.42266437
55	Belarus	0.34145316	Costa Rica	0.42107627	Saudi Arabia	0.41851676
56	Costa Rica	0.32201701	Belarus	0.41381541	Russian Federation	0.41788104
57	Sri Lanka	0.31803155	Russian Federation	0.41371772	Greece	0.41109794
58	Bosnia and Herzegovina	0.309847	Uruguay	0.40895012	Macedonia, FYR	0.39762917
59	Montenegro	0.29164797	Turkey	0.40437108	Brazil	0.39142197
60	Bulgaria	0.29155305	Bulgaria	0.40033787	Serbia	0.3865419
…						
100	West Bank and Gaza	0.14231104	Honduras	0.17292187	Ethiopia	0.15942949
101	Uganda	0.14114372	Jordan	0.17142873	Mozambique	0.15591694
102	Jordan	0.14052431	Tunisia	0.1707871	Algeria	0.15180664
103	Honduras	0.12916216	Armenia	0.16267568	Haiti	0.14704004
104	Uzbekistan	0.12291671	Angola	0.15456079	Kyrgyz Republic	0.14280415
105	Armenia	0.12288269	Uzbekistan	0.15273209	Azerbaijan	0.14254785
106	Azerbaijan	0.12235593	Cambodia	0.14317246	Philippines	0.14220303
107	Tanzania	0.12073816	Bangladesh	0.13955806	Gabon	0.14218831
108	Indonesia	0.11980094	Mauritania	0.13751817	Paraguay	0.1375798
109	Iraq	0.11466344	Nicaragua	0.13510107	El Salvador	0.13543274
110	El Salvador	0.11461792	Moldova	0.12488277	Benin	0.12894543
…						
140	Madagascar	0.01253937	Burundi	0.02189513	Afghanistan	0.02131184
141	Burundi	0.0112908	Madagascar	0.01899051	South Sudan	0.01085947
142	Guinea	0.00959252	Niger	0	Chad	0.00848196
143	Congo, Dem. Rep.	0.00620072			Madagascar	0.0062731
144	Niger	0			Niger	0

[19] Full rank in Appendix.

The index provides us with a unique perspective about FI. As mentioned in the beginning of this chapter, if the purpose of FI is to include individuals, macroeconomic variables that have been used to construct indexes are not suitable. Comparing my results to Sarma's (2016), which is the most complete ranking using only macroeconomic variables, some differences can be found. Table 6 presents the comparison among the top 10 countries in both indexes.

Table 6. *Ranking comparison*

Rank	GRFI 2011	Sarma 2011	Camara and Tuesta 2011	GRFI 2014	Sarma 2014
1	Sweden	Switzerland	Korea	Norway	Switzerland
2	New Zealand	Portugal	Spain	New Zealand	San Marino
3	Finland	Spain	Portugal	Canada	Japan
4	Australia	Japan	Belgium	Sweden	Portugal
5	Canada	United Kingdom	Japan	Finland	Malta
6	Denmark	Malta	Canada	Australia	Spain
7	Netherlands	Korea	France	United Kingdom	France
8	Luxembourg	France	United States	Luxembourg	Belgium
9	United States	Greece	Australia	Denmark	Greece
10	Belgium	Belgium	New Zealand	Israel	Russia

First, the most financially included countries in the GRFI, such as Sweden and New Zealand, are not part of the analysis, while countries with important financial centres, such as the USA, Luxemburg or Singapore, are also not present.[20] Second, by selecting macroeconomic variables to analyse individual's financial inclusion, results are inflated for several countries. For 2011, the top countries were: Switzerland, Portugal and Spain, and, for 2014, Switzerland, San Marino and Japan. Unfortunately, the Findex doesn't provide data for Switzerland in 2011, but Japan, Spain and Portugal are far from being the most financially included countries in the world when analysing from an individual perspective.

When comparing to Camara and Tuesta's (2014) ranking, their usage dimension is quite similar to my results, as they also select 2014 Findex information to construct this index (top countries are New Zealand, Sweden and Finland). However, the final raking includes again macroeconomic variables, which bias the results.[21] Thus, when adding the results of the three dimensions (access, usage and barriers), their rank is closer to Sarma's (2016). The most financially included countries in this study are Korea, Spain and Portugal. Sweden and Finland, on the other hand, are down to the 16th and 19th positions.

Table 7 displays a comparative sample of the differences among countries that have been placed in the top positions of the FI indexes. Portugal has a higher level of credit with respect to GDP than Sweden and Finland, even if its population has less access to credit cards and loans from financial institutions. This can represent that either this amount of credit has been designated to firms and other financial institutions, or that the few individuals that have access to credit are the ones holding this amount. Spain does surpass Sweden in credit card ownership

[20] According to the Global Financial Centres Index, the world's top financial hubs were London, New York, Hong Kong and Singapore in 2011 and 2014.
[21] A comparison to Aslan *et al.* (2017) would be more desirable, as they only use the Findex dataset. However, the paper doesn't provide enough information on the scores for financial inclusion, nor does it rank countries.

and Finland in formal loans in 2014, but the country still lags behind in general. Moreover, the debt crisis that affected Portugal and Spain seems not to be taken into account, even with its effect on GDP reduction in 2011 (thus pushing an increase in total credit as percentage of GDP, for instance).

Likewise, Portugal and Spain have at least double of the amount of bank branches than Sweden and Finland. This, however, shouldn't be the defining variable as the latter could have a highly automatized system, in which individuals can use their cards to pay in stores or online, thus not needing the physical presence of banks. Therefore, the use of micro-level data seems to be more reliable for creating an index that reflects the financial inclusion of individuals.

Table 7. *Country comparison of selected variables (2011 and 2014)*

		Finland		Sweden		Portugal		Spain	
		2011	2014	2011	2014	2011	2014	2011	2014
Macro	Domestic credit provided by financial sector (% of GDP)	189.43	164.41	152.47	156.68	204.79	173.73	248.93	211.25
	Commercial bank branches (per 100,000 adults)	15.09	12.06	21.70	21.10	63.94	53.39	88.22	69.68
	Depositors with commercial banks (per 1,000 adults)	2294.86	2222.02	3856.01	4242.81	2538.17	2358.41	2176.60	1987.04
Micro	Account at a financial institution	98.60	100.00	98.50	99.70	85.31	91.61	92.61	98.30
	Credit card ownership	72.49	68.64	57.04	51.47	39.53	36.07	48.14	63.40
	Loan from a financial institution	22.97	18.40	24.47	28.71	7.95	10.99	11.14	19.88

6. Conclusion

To sum up, an index using micro-level information is necessary to place where individuals are with respect to FI. Using macroeconomic variables, as seen above, leads to a misleading outcome, thus inducing a biased assessment. In order to generate the scores, we decide on using the MCA method, which is the most appropriate one to deal with categorical variables, which is the case of our sample.

Through a visual representation, we perceive that high income countries are clearly in advantage when it comes to FI, with a majority of the population having access to basic financial services and credit. On the other hand, most developing countries' individuals have low access to formal financial services, but are more indebted than individuals in developed countries, in particular for education and health care purposes.

Through estimations, we notice that there are differences in the level of FI between developed and developing countries. Furthermore, while education and income is not so significant in developed countries, they are stronger determinants of the level of FI in developing ones. These differences are also observed by the Global Ranking of Financial Inclusion, in which the position of countries in the index suggests that those with high income per capita besides low level of income inequality are the ones with a more inclusive financial system.

Thus, while the limitation of the data hinder a more complete assessment of FI worldwide, this index is a first step into creating over time comparison between individuals using micro-data, and assessing the implications of individual's characteristics and their placement in a world ranking.

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Appendix

Table A.1: Summary of approaches of existing indexes of financial inclusion

	Paper	Methodology	Sample	Dimensions	Composition
1	Amidžić, Massara and Mialou (2014)	Factor analysis and weighted geometric mean	23 to 31 countries (depends on the year)	Access (weight 0.52 for 2009 and 0.51 remainder)	Number of ATMs per 1,000 sq. km; Number of branches of other depository corporations (ODCs)
				Usage (0.48 for 2009 and 0.49 remainder)	Number of resident households depositors with ODCs per 1,000 adults; Number of resident households borrowers with ODCs per 1,000 adults
2	Aslan *et al.*, (2017)[22]	Joint correspondence analysis (JCA)	129 countries	Access	Individual has an account (composite indicator)/ debit card/ credit card Moreover, for 2014: if has a debit card, card in own name
				Usage	Individual has saved/borrowed from a financial institution in the past 12 months; uses electronic payments; has used mobile phone to pay bills/ send/ receive money; has a loan from financial institution for home/land purchase or construction Moreover, for 2014: used debit card/credit card in the past 12 months; made deposit/withdrawal in past 12 months; made transaction with mobile phone; made internet payments
				Other	Possibility of coming up with emergency funds
3	Camara and Tuesta (2014)	Two-stage principal component analysis (PCA)	82 countries	Access	ATM per 100,000 adults; commercial bank branches per 100,000 adults; ATMs per 1,000 km^2; commercial bank branches per 1,000km^2
				Usage	Individual has a bank account/ mobile service/ debit card/ credit card/ savings/ loans; someone else in household has an account
				Barrier	Distance; affordability; documentation; trust
4	Chakravarty and Pal (2013)	Axiomatic distance-based approach	India	Access	Bank branches per 1,000km^2; Bank branches per lakh[23] adults; deposit account per 1,000 adults; Number of loans per 1,000 adults; deposit-income ratio; credit-income ratio
5	Honohan (2008)	Fitted values (OLS)	162 countries	Access	Number of bank accounts per 100 adults, percentage of access (household survey); Number of accounts at microfinance institutions per 100 adults
6	Sarma (2016)	Axiomatic distance-based approach	57 to 128 (depends on the year)	Access	Number of deposit bank account per 1,000 adults
				Availability	Number of bank branches + Number of registered mobile money service providers agents (2/3 weight); Number of ATMs (1/3 weight)

[22] The study does not define the dimensions, so I allocate them on my own discretion to make it comparable across studies.
[23] Lakh is a unit in the Indian numbering system equal to one hundred thousand

				Usage	Total volume of credit/ deposit/ mobile money transactions as % of GDP
7	Piñeyro (2013)	PCA	Mexico	Access	Number of branches and banking agents; bank, co-op and microfinance, banking agents' presence; Number of ATMs; Number of point of services
				Usage	Number of deposits, loans and credit accounts; proportion of bank, co-op and microfinance deposit and credit accounts
				Financial Education	Average adult education in years; percentage of population with lack of education; percentage of illiterate adults; adults with incomplete elementary school
				Consumer protection	Number of technical and legal advices and disputes
				Social development	Average income per municipality; percentage of non-poor and non-vulnerable population; incidence of poverty

Table A.2. Description of variables for Findex 2011, 2014 and 2017

Variable	2011	2014	2017
Account at a financial institution	Denotes the percentage of respondents with an account (self or together with someone else) at a bank, credit union, another financial institution (e.g., cooperative, microfinance institution), or the post office (if applicable) including respondents who reported having a debit card.	Respondents who report having an account (by themselves or together with someone else) at a bank or another type of financial institution	Refers to respondents who reported having an account (by themselves or together with someone else) at a bank or another type of financial institution
Debit card ownership	Denotes the percentage of respondents with a debit card.	Respondents who report having a debit card.	Refers to respondents who reported having a debit card
Credit card ownership	Denotes the percentage of respondents with a credit card.	Respondents who report having a credit card.	Refers to respondents who reported having a credit card
Mobile money account	[Composite variable created by author] 1. Mobile phone used to pay bills: denotes the percentage of respondents who report using a mobile phone to pay bills in the past 12 months (q15a1a) 2. Mobile phone used to send money: denotes the percentage of respondents who report using a mobile phone to send money in the past 12 months (q15a1b) 3. Mobile phone used to receive money: denotes the percentage of respondents who report using a mobile phone to receive money in the past 12 months (q15a1c)	Respondents who report personally using a mobile money service in the past 12 months	Refers to respondents who reported personally using a mobile money service in the past 12 months.
Loan from financial institution in past 12 months	Denotes the percentage of respondents who report borrowing any money from a bank, credit union, microfinance institution, or another financial institution such as a cooperative in the past 12 months.	Respondents who report borrowing any money from a bank or another type of financial institution in the past 12 months.	Refers to respondents who reported borrowing any money from a bank or another type of financial institution, or using a credit card, in the past 12 months
Loan from a store (store credit) in past 12 months	Denotes the percentage of respondents who borrowed any money in the past 12 months from a store by using installment credit or buying on credit.	Respondents who report borrowing any money from a store by using installment credit or buying on credit in the past 12 months.	Denotes respondents who report borrowing any money from a store by using installment credit or buying on credit in the past 12 months
Loan to start, operate, or expand a farm or business in past 12 months	N/A	Respondents who report borrowing any money to start, operate, or expand a farm or business in the past 12 months.	
Loan for school fees	Denotes the percentage of respondents who report having an outstanding loan to pay for school fees.	Respondents who report borrowing any money for education or school fees in the past 12 months.	Denotes respondents who report borrowing any money for education or school fees in the past 12 months
Loan for medical purposes	Denotes the percentage of respondents who report having an outstanding loan for emergency or health purposes.	Respondents who report borrowing any money for health or medical purposes in the past 12 months.	Denotes respondents who report borrowing any money for health or medical purposes in the past 12 months.
Loan for home purchase	Denotes the percentage of respondents who report having an outstanding loan to purchase their home or apartment.	Respondents who report having an outstanding loan from a bank or another type of financial institution to purchase a home, an apartment, or land.	Refers to respondents who reported having an outstanding loan (by themselves or together with someone else) from a bank or another type of financial institution to purchase a home, an apartment, or land.
Savings at a financial institution in the past 12 months	Denotes the percentage of respondents who report saving or setting aside any money by using an account at a formal financial institution such as a bank, credit union, microfinance institution, or cooperative in the past 12 months.	Respondents who report saving or setting aside any money by using an account at a bank or another type of financial institution in the past 12 months.	Refers to respondents who reported saving or setting aside any money at a bank or another type of financial institution in the past 12 months.

In the Findex 2011 dataset, q1 or "account" is defined as a composite indicator based on the values of q1a ("has an account at a financial institution") and q1b ("has an account at the post office"). However, it is not clear how this composite indicator q1 has been build. When analysing the variable in detail, it is possible to see that it overestimates account ownership of several individuals. Table A.1 provides a sample of where q1 has been designated a positive value, although q1a and q1b were either missing or negative.

Table A.3. Sample of account ownership measurements from the Findex 2011 database

ID	Economy	Account at financial institution	Account at the post office	Account (composite indicator)
82522	LUX	no	no	yes
82523	LUX	refused	refused	yes
82524	LUX	refused	refused	yes

Due to this measurement failure, I decide to use only "Account at financial institution" instead of the provided composite indicator q1 in my analysis.

Another issue that has risen while analysing the data is that very few countries use mobile phones for financial purposes. These, however, have a higher usage of this device. When using three different variables to assess similar activities, countries such as Kenya, where 71% of population have used a mobile to receive money, was overestimated with respect to financial inclusion. I decide to create a new variable "Mobile Account" (q15a1d), in which if any of the three variables were positive, the new variable would also be positive. This is also an important way of comparing the results of the Findex 2011 with its latest versions.

Table A.4. Summary statistics for mobile usage variables from the Findex 2011 database

Variable	Observation	Mean	Standard deviation
Mobile phone to pay bills	148,328	.021	.145
Mobile phone to send money	148,261	.036	.187
Mobile phone to receive money	148,268	.049	.217

Table A.5. The Global Ranking for Financial Inclusion (GRFI)

Rank	GRFI 2011	Score value	GRFI 2014	Score value	GRFI 2017	Score value
1	Sweden	1	Norway	1	Norway	1
2	New Zealand	0.96096832	New Zealand	0.94831634	Canada	0.93925679
3	Finland	0.94250089	Canada	0.93279457	New Zealand	0.88149965
4	Australia	0.9352718	Sweden	0.92034501	Sweden	0.88137692
5	Canada	0.91992617	Finland	0.88955343	Luxembourg	0.8646971
6	Denmark	0.90344626	Australia	0.86555076	Finland	0.84391421
7	Netherlands	0.87696278	United Kingdom	0.85406357	Australia	0.84148878
8	Luxembourg	0.87541926	Luxembourg	0.84831798	Denmark	0.82942843
9	United States	0.82916677	Denmark	0.83552569	United States	0.82450575
10	Belgium	0.81719321	Israel	0.81867319	United Kingdom	0.81950557
11	United Kingdom	0.81629759	United States	0.81045282	Netherlands	0.80449718
12	Ireland	0.81413764	Spain	0.80914938	Switzerland	0.80398142
13	Germany	0.7965371	Japan	0.80450153	Belgium	0.78008246
14	Kuwait	0.78893507	Netherlands	0.79477501	Japan	0.77604544
15	Austria	0.78590292	Germany	0.7886911	Singapore	0.77421969
16	Malta	0.74763733	Belgium	0.78656203	Germany	0.7639876
17	France	0.7442714	Switzerland	0.78238755	Spain	0.76288992
18	Korea, Rep.	0.73844951	Singapore	0.75634569	Korea, Rep.	0.75242078
19	Hong Kong SAR, China	0.73831952	Ireland	0.7510131	Austria	0.73134565
20	Spain	0.70270562	France	0.73900843	Ireland	0.72926533
21	Slovenia	0.69991827	Korea, Rep.	0.72935116	Israel	0.7271834
22	Estonia	0.69368589	Austria	0.72837126	Hong Kong SAR, China	0.70971853
23	Cyprus	0.64723516	Hong Kong SAR, China	0.70550483	France	0.70648521
24	Singapore	0.64637637	Estonia	0.70103687	Taiwan, China	0.69398451
25	Japan	0.63565397	Taiwan, China	0.68726677	Malta	0.69273674
26	Israel	0.61907375	Slovenia	0.68567157	Estonia	0.68559504
27	Taiwan, China	0.61199307	Croatia	0.67272925	Slovenia	0.66750938
28	Portugal	0.60734564	Malta	0.66722333	Italy	0.66681468
29	Croatia	0.58701515	Bahrain	0.63264894	United Arab Emirates	0.62745428
30	Slovak Republic	0.56502759	United Arab Emirates	0.62449825	Slovak Republic	0.61776465
31	Czech Republic	0.54856116	Latvia	0.59872383	Portugal	0.60751122
32	Latvia	0.5315972	Slovak Republic	0.59299129	Bahrain	0.58664274
33	Qatar	0.51654863	Italy	0.58415282	Czech Republic	0.57543921
34	Trinidad and Tobago	0.50384617	Czech Republic	0.57993633	Iran, Islamic Rep.	0.57345146
35	Oman	0.49550769	Mongolia	0.57589823	Poland	0.56337851
36	Mauritius	0.49397266	Portugal	0.5618881	Croatia	0.54796529
37	United Arab Emirates	0.49397257	Mauritius	0.54165119	Latvia	0.52800918
38	Turkey	0.48098776	Kuwait	0.5372805	Malaysia	0.5267356
39	Hungary	0.47468939	Cyprus	0.5229646	Kuwait	0.5199967
40	Bahrain	0.47434029	Malaysia	0.50507802	Mauritius	0.512734
41	Mongolia	0.47251955	China	0.47311586	Mongolia	0.50862461
42	Lithuania	0.46399641	Lithuania	0.47108299	Trinidad and Tobago	0.49614418
43	Thailand	0.44469702	Puerto Rico	0.46933654	Cyprus	0.49046832
44	Greece	0.41529971	Thailand	0.46548614	China	0.48918739
45	Jamaica	0.40991077	Poland	0.45972592	Turkey	0.48424283

46	Malaysia	0.39760131	South Africa	0.45740616	Belarus	0.48403424
47	Poland	0.39690471	Brazil	0.45023739	Lithuania	0.4820742
48	Italy	0.39568463	Chile	0.44777459	Thailand	0.47021911
49	Macedonia, FYR	0.38820237	Hungary	0.44555631	Namibia	0.45244986
50	China	0.38146341	Macedonia, FYR	0.44174486	Chile	0.44856235
51	Brazil	0.36063302	Saudi Arabia	0.4406527	Bulgaria	0.43778038
52	Saudi Arabia	0.36016682	Greece	0.44059163	Hungary	0.4362646
53	Serbia	0.35669553	Jamaica	0.43168354	Venezuela, RB	0.42537856
54	South Africa	0.35139075	Serbia	0.43029857	Uruguay	0.42266437
55	Belarus	0.34145316	Costa Rica	0.42107627	Saudi Arabia	0.41851676
56	Costa Rica	0.32201701	Belarus	0.41381541	Russian Federation	0.41788104
57	Sri Lanka	0.31803155	Russian Federation	0.41371772	Greece	0.41109794
58	Bosnia and Herzegovina	0.309847	Uruguay	0.40895012	Macedonia, FYR	0.39762917
59	Montenegro	0.29164797	Turkey	0.40437108	Brazil	0.39142197
60	Bulgaria	0.29155305	Bulgaria	0.40033787	Serbia	0.3865419
61	Kenya	0.27620241	Montenegro	0.39027551	Costa Rica	0.37650499
62	Chile	0.27502376	Sri Lanka	0.37997124	Kazakhstan	0.36557913
63	Russian Federation	0.27201539	Kenya	0.37630805	Ukraine	0.35789499
64	Ukraine	0.26252007	Venezuela, RB	0.35933563	Sri Lanka	0.34642801
65	Kazakhstan	0.26182249	Romania	0.35420743	Romania	0.33945182
66	Venezuela, RB	0.25928202	Namibia	0.35260212	Montenegro	0.33325347
67	Lebanon	0.25637752	Botswana	0.34440362	Georgia	0.33168852
68	Romania	0.25582463	Ukraine	0.34081453	Dominican Republic	0.32081565
69	Angola	0.24272709	Dominican Republic	0.33671626	Kenya	0.31835681
70	Swaziland	0.23971531	Lebanon	0.33468232	India	0.29989016
71	Zimbabwe	0.23771937	Argentina	0.3286452	South Africa	0.29988062
72	Dominican Republic	0.23501337	Kazakhstan	0.31658539	Lebanon	0.29417101
73	Kosovo	0.23228769	Bosnia and Herzegovina	0.31110099	Bosnia and Herzegovina	0.28984755
74	Argentina	0.2263739	Bolivia	0.30465129	Armenia	0.27813569
75	Ecuador	0.21999465	Belize	0.29743445	Bolivia	0.26354578
76	Colombia	0.21202242	Mexico	0.27925128	Argentina	0.2633214
77	Morocco	0.21171096	Nigeria	0.27834114	Libya	0.25325578
78	Uruguay	0.20564911	Colombia	0.27808127	Indonesia	0.2520397
79	Botswana	0.19306757	Kosovo	0.27603966	Kosovo	0.2513822
80	Bolivia	0.19269742	Panama	0.2727749	Ecuador	0.23321585
81	Bangladesh	0.19189334	Ecuador	0.26465815	Colombia	0.22597498
82	Nigeria	0.1910523	Georgia	0.26460409	Tajikistan	0.22306877
83	Panama	0.18793948	El Salvador	0.24691129	Moldova	0.22225054
84	Georgia	0.17970614	Indonesia	0.24364223	Panama	0.22201839
85	Albania	0.1796457	India	0.22749662	Jordan	0.22000778
86	Syrian Arab Republic	0.17537706	Guatemala	0.21988212	Peru	0.21496899
87	Philippines	0.17503527	Vietnam	0.21548529	Vietnam	0.20506708
88	Lao PDR	0.1674588	Algeria	0.21460278	Botswana	0.20015088
89	Mexico	0.16719061	Uganda	0.21426903	Ghana	0.19636932
90	Ghana	0.16220956	Peru	0.21065201	Nigeria	0.19308834
91	Guatemala	0.15418194	Albania	0.19948435	Tunisia	0.19181061
92	Peru	0.1540442	Nepal	0.19429953	Nepal	0.18970467
93	India	0.15340784	Philippines	0.19208443	Albania	0.18253383

94	Zambia	0.15153426	Azerbaijan	0.19185382	Turkmenistan	0.18129578
95	Vietnam	0.15090699	Ghana	0.19152927	Honduras	0.18071052
96	Nepal	0.14991188	Rwanda	0.19070219	Guatemala	0.17481612
97	Rwanda	0.14783908	Bhutan	0.18403405	Uganda	0.17442027
98	Algeria	0.14536755	Zambia	0.17932135	Zambia	0.16780618
99	Paraguay	0.14299443	Gabon	0.17591932	Mexico	0.16161413
100	West Bank and Gaza	0.14231104	Honduras	0.17292187	Ethiopia	0.15942949
101	Uganda	0.14114372	Jordan	0.17142873	Mozambique	0.15591694
102	Jordan	0.14052431	Tunisia	0.1707871	Algeria	0.15180664
103	Honduras	0.12916216	Armenia	0.16267568	Haiti	0.14704004
104	Uzbekistan	0.12291671	Angola	0.15456079	Kyrgyz Republic	0.14280415
105	Armenia	0.12288269	Uzbekistan	0.15273209	Azerbaijan	0.14254785
106	Azerbaijan	0.12235593	Cambodia	0.14317246	Philippines	0.14220303
107	Tanzania	0.12073816	Bangladesh	0.13955806	Gabon	0.14218831
108	Indonesia	0.11980094	Mauritania	0.13751817	Paraguay	0.1375798
109	Iraq	0.11466344	Nicaragua	0.13510107	El Salvador	0.13543274
110	El Salvador	0.11461792	Moldova	0.12488277	Benin	0.12894543
111	Liberia	0.10875637	West Bank and Gaza	0.12324434	Lao PDR	0.12881601
112	Malawi	0.10660087	Myanmar	0.11680176	Bangladesh	0.12879111
113	Lesotho	0.10520069	Tanzania	0.11485886	Togo	0.12865184
114	Haiti	0.10153848	Kyrgyz Republic	0.1061644	Rwanda	0.1284568
115	Moldova	0.09481389	Ethiopia	0.10427323	Cambodia	0.12700839
116	Sierra Leone	0.09257607	Malawi	0.10121818	Egypt, Arab Rep.	0.12692249
117	Mauritania	0.08945227	Haiti	0.09795293	Nicaragua	0.12383792
118	Nicaragua	0.08667465	Zimbabwe	0.09122999	Lesotho	0.12205341
119	Chad	0.08515136	Congo, Rep.	0.08921291	Burkina Faso	0.11439942
120	Comoros	0.08236081	Sierra Leone	0.08767383	Uzbekistan	0.10673666
121	Djibouti	0.07931998	Benin	0.08699986	Cameroon	0.10297137
122	Afghanistan	0.07432321	Egypt, Arab Rep.	0.0867934	Zimbabwe	0.10108162
123	Gabon	0.07340191	Iraq	0.08415885	Myanmar	0.09554914
124	Sudan	0.06982932	Senegal	0.07588271	Malawi	0.09127819
125	Cameroon	0.06176766	Ivory Coast	0.07162809	Morocco	0.08925539
126	Congo, Rep.	0.05576349	Burkina Faso	0.06993922	West Bank and Gaza	0.08518209
127	Pakistan	0.05261227	Sudan	0.06991885	Mauritania	0.07954754
128	Burkina Faso	0.04952682	Somalia	0.0577886	Liberia	0.07940972
129	Cambodia	0.04926754	Togo	0.05757565	Tanzania	0.07210979
130	Egypt, Arab Rep.	0.04388884	Cameroon	0.05622087	Congo, Rep.	0.07113567
131	Kyrgyz Republic	0.03992744	Pakistan	0.05397604	Mali	0.07110111
132	Yemen, Rep.	0.03981394	Afghanistan	0.05324388	Senegal	0.07027806
133	Togo	0.03730064	Congo, Dem. Rep.	0.04325277	Guinea	0.04372271
134	Benin	0.03665847	Mali	0.04298539	Central African Rep.	0.03535364
135	Mali	0.03013374	Tajikistan	0.04245162	Iraq	0.03373666
136	Turkmenistan	0.02776752	Chad	0.04008637	Pakistan	0.03308754
137	Senegal	0.02726529	Guinea	0.03515873	Cote d'Ivoire	0.02857214
138	Tajikistan	0.02328606	Yemen, Rep.	0.03467888	Sierra Leone	0.02465378
139	Central African Repub.	0.01278288	Turkmenistan	0.03171131	Congo, Dem. Rep.	0.02385792
140	Madagascar	0.01253937	Burundi	0.02189513	Afghanistan	0.02131184
141	Burundi	0.0112908	Madagascar	0.01899051	South Sudan	0.01085947

142	Guinea	0.00959252	Niger	0	Chad	0.00848196
143	Congo, Dem. Rep.	0.00620072			Madagascar	0.0062731
144	Niger	0			Niger	0