Socio-economic determinants of financial inclusion: an evaluation with a microdata multidimensional index

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ABSTRACT Financial inclusion is a central theme in development policy. While it involves changes at the individual level and comprises several interrelated financial activities, most existing measures rely on macroeconomic variables. We construct an alternative index of financial inclusion using the World Bank Findex – a microdata dataset with 451,372 observations. Applying it, we first analyse the socio-economic determinants of financial inclusion. Second, we propose a new country ranking of financial inclusion. Our findings comprise three features. First, we do not find evidence of a gender gap in low- and middle-income countries. Second, richer individuals display higher levels of financial inclusion. Third, countries with high self-employment rates exhibit lower levels of financial inclusion. Our results suggest that financial inclusion is more related to income and employment status than gender disparities, which could lead to a different approach from policymakers on promoting the inclusion of the poor into the formal financial system.

Keywords: financial inclusion; multidimensional measurement; index; multiple correspondence analysis; low- and middle-income countries; high-income countries

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1. Introduction

In 2015, the World Bank launched an initiative to include all men and women in the formal financial system by 2020. Financial inclusion (FI) is argued to reduce poverty and promote economic growth. Cross-country comparisons have been conducted to assess the effectiveness of the policy as well as to compare the relationship between FI and other socio-economic measures, such as the human development index, educational levels or income inequality (Bozkurt, Karakuş, and Yildiz 2018; Park and Mercado 2018; Sarma and Pais 2011; Wang and Guan 2017). Most existing research uses aggregate data to construct indexes of FI, which may not fully reflect individuals' access to and usage of the financial system. This article contributes to the measurement of FI by constructing a microdata index using the World Bank's Findex dataset with 451,372 observations. This alternative index is used to (i) analyse the socio-economic determinants of FI, (ii) generate a country-level ranking, and (iii) assess the macroeconomic correlates of FI. We notice key disparities between aggregate and individual-level indexes of FI, with consequences for evaluating determinants and effects of such policy.

FI has two strands of literature: one from an economic geography perspective and another based on the financial development (FD) literature. Initially, discussions of FI made use of comprehensive literature on financial exclusion, focusing on low-income individuals and minority groups. Creditworthy individuals from ethnic minorities were often denied formal credit, and poor communities lacked the presence of financial institutions, exacerbating uneven regional development (Dymski 1995; Leyshon and Thrift 1995; Pollard 1996). However, more recent studies on FI have built on the financial development (FD) literature.[1] According to this approach, FD is conducive to economic growth as it reduces costs of financial services and provides more diverse vehicles for savings and financing economic activity (Claessens and Laeven 2003; Khan and Senhadji 2000; Levine 1997). More recent studies claim that financial market frictions generate 'persistent income inequality and poverty traps' (Demirgüç-Kunt, Beck, and Honohan 2008:24). Thus, it is argued that a more developed financial system could reduce poverty and income inequality '[…] by improving the efficiency of capital allocation' and 'by relaxing credit constraints that more extensively restrain the poor' (Beck, Demirgüç-Kunt, and Levine 2007:28).

FI and FD are primarily linked through their theoretical frameworks. While somewhat overlooked in FI research, both kinds of literature are, to a great degree, based on the work by Aghion and Bolton (1997), Banerjee and Newman (1993) and Galor and Zeira (1993). Drawing on the theoretical models proposed in these studies, FI studies claim that credit can reduce poverty through two mechanisms: human capital investment and entrepreneurship. In addition, equal access to finance is also expected to reduce income inequality as the poor will have the same financial opportunity as the rich to invest in human capital and business.[2] Finally, it is assumed that FI allows the poor to mobilise savings and obtain credit to smooth consumption over time (Fungáčová and Weill 2015; Li 2018; World Bank 2014; Zhang and Posso 2019; Zins and Weill 2016).

The second link between FI and FD, which is the focus of this article, corresponds to how FD and FI are measured. FD studies select aggregate variables to measure the depth of financial systems, such as the number of ATMs per 1000km^2 and credit to GDP ratios (Beck

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[1] Another stream of the literature identifies FI as a rebranding of microfinance in the mid-2000s (Bateman 2014; Dafe 2020; Mader 2018; Mader and Sabrow 2015).

[2] Key discussions on the issues of FI and entrepreneurship in developing countries can be found in Bateman and Chang (2012), Kalpana (2005) and Taylor (2012).

et al. 2004; Honohan 2004; Rewilak 2017). Cross-country empirical studies using FI indexes select similar macroeconomic variables (Amidžić, Massara, and Mialou 2014; Chakravarty and Pal 2013; Honohan 2008; Piñeyro 2013; Sarma 2016).[3] Nonetheless, as FI targets financial services at the individual level, aggregate data may distort the actual FI level of a country's population. For instance, private credit to GDP ratios may be driven by a small number of highly indebted units and thus imperfectly reflect how many individuals have access to bank accounts or credit instruments.

The limitations of aggregate indexes are considered by another stream of the FI literature, which uses microdata to evaluate the effects of FI. However, these studies do not provide multidimensional indexes. They assess the determinants of FI by performing maximum likelihood estimations with univariate indicators at multiple points in time, such as account ownership, savings or formal credit, or using FI as a binary variable that represents a successful outcome if any financial service is used (Allen et al. 2016; Fungáčová and Weill 2015; Murendo et al. 2021; Wang and Guan 2017; Zins and Weill 2016). Their findings, e.g. that the poor, self-employed and women have a lower likelihood of having a bank account, are a first step toward understanding certain aspects of FI. Nonetheless, analysing single FI indicators in isolation creates difficulties in identifying a multidimensional policy.

Addressing these issues, three studies use a multidimensional approach based on micro-economic indicators. Camara and Tuesta (2014) apply principal correspondence analysis (PCA) for analysing the 2011 Findex database but combine the microdata results to aggregate variables, yielding scores very similar to standard macroeconomic indexes. Similarly, Bozkurt et al. (2018) utilise the Findex dataset for 2011 and 2014 to build an index based on Sarma's

[3] Further details on selected variables and methods of multidimensional indexes of FI in the Appendix A.1 (Table A.1).

(2016) axiomatic distance-based approach, but also add macroeconomic variables, boosting results of countries that might not have a strong individual-level FI (more on this issue in the next section). On the other hand, Aslan, Deléchat, Newiak, and Yang (2017) conducted a joint correspondence analysis of the same dataset for 2011 and 2014. However, as different variables are selected for each year, the results lack comparability over time. Thus, estimations using such indexes may display an inaccurate reflection of the determinants and effects of FI and prevent cross-country and inter-temporal assessment.

Considering the shortcomings of existing measurements in the literature, this article aims to provide an alternative by creating a multidimensional index of FI using only microdata. Multiple correspondence analysis (MCA) is employed to reduce the dimensions of 11 categorical variables drawn from the Global Findex database for 2011, 2014 and 2017 (Demirgüç-Kunt and Klapper 2012b). Defined as the access to and use of deposits, payments, credit, insurance, and savings by individuals provided by financial institutions, we hold that FI must encompass all these aspects, as each plays a distinct role in including individuals in the formal financial system.[4]

Besides creating a new multidimensional index, we provide two further contributions to existing research on FI. First, we conduct a repeated cross-section analysis of socio-economic determinants of FI for 451,372 individuals from low- and middle-income countries (LMICs) and high-income countries (HICs) using the Findex waves of 2011, 2014 and 2017. Second, we construct a country ranking of FI based on the micro-level index and assess its macroeconomic correlates. Our results provide a qualification of existing measurements of FI, as well as provide a first step into evaluating the effects of FI on development goals.

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[4] While the financial inclusion policy aims at including individuals into the formal financial system, the role of informal credit in developing countries still plays an important role (Bouquet, Morvant-Roux, and Rodriguez-Solis 2015; Guérin et al. 2013). However, such investigation is out of the scope of this paper.

Our key findings comprise three aspects of FI: gender, income and employment status. First, we find that the often-discussed gender gap in FI is not present in LMICs in general. In fact, the opposite is found: women in LMICs have higher levels of FI, in particular those with fewer years of formal education. Interestingly, women in HICs do display higher disparities in terms of FI – a phenomenon that is not commonly discussed in the literature. Second, individuals in the upper-income quintiles and with high levels of education also display higher levels of FI in LMICs. By contrast, we find little evidence of such effects in HICs, suggesting that income and education may not be a vital determinant of FI in those countries. We further find a negative correlation between FI and GDP per capita at the macro-level (Pearson coefficient of 0.874 in 2017) as well as personal income distribution (-0.46). Third, we find that countries with high rates of self-employment perform worse in the FI ranking. Moreover, women in the workforce have more access to and usage of financial services. Overall, these findings suggest that income and employment status may be more essential factors in determining the level of FI than gender.

The article is structured as follows: Section 2 discusses the differences in measuring FI using macro- or microdata. Section 3 introduces the dataset and selected variables, while Section 4 describes the construction of the new FI index. Section 5 investigates socio-economic determinants of FI, whereas Section 6 creates a country ranking of FI and examines its relationship to macroeconomic phenomena. The last section concludes.

2. On the use of macro- and microdata for measuring financial inclusion

As a multidimensional policy, FI has often been measured through indexes. These, however, have been usually constructed using macroeconomic variables, such as domestic credit provided by the financial sector as a share of GDP, the number of commercial bank branches per 100,000 adults or the number of automated teller machines (ATMs) per 1,000 square kilometres (e.g. Amidžić, Massara, and Mialou 2014; Chakravarty and Pal 2013; Honohan 2008; Piñeyro 2013; Sarma 2016). Nonetheless, these variables might be inappropriate for accurately measuring FI for two reasons.

First, while aggregated information can be useful for a cross-country and over-time comparison, it can also give an incomplete picture of FI (Klapper and Singer 2017; Pesqué-Cela et al. 2021; Zhang and Posso 2019). One example is the number of ATMs and bank branches per 100,000 adults (or 1,000 km^2). As many countries have digitalised in recent years, there has been a reduction of such physical presence, even in countries with high FI levels (Sarma 2016). According to Demirgüç-Kunt et al. (2018), 29% of adults used the internet to pay bills or purchase goods online worldwide in 2017 – ranging from 68% in HICs to 11% in LMICs, excluding China. Thus, the need for bank branches or ATMs seems to have diminished, and using it as a measure for individuals' FI could be misleading, especially within HICs.

Second, aggregate variables may not correspond to individuals' actual access and use of the financial system. For instance, the volume of credit as a share of GDP and other national-level financial development measurements can also be deceptive as credit can be concentrated in large firms rather than in loans for individuals. Demirgüç-Kunt and Klapper (2013:290) compare Vietnam and Czech Republic as examples. In Vietnam, the amount of domestic credit given 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 only 55% of

GDP, although 81% of adults have a bank account. Thus, by including such indicators, the index may penalise countries with low levels of indebtedness, besides not fully grasping the individual-level credit usage.

Whereas one could construct a more comprehensive index that would consider both the micro- and macrodata, this approach has its limitations. Camara and Tuesta (2014) combine the individual data from the 2011 Findex with aggregate data from the IMF's Financial Access Survey using a two-stage PCA method. Whereas the study selects fewer variables and fewer countries than the present article, the country ranking for "usage" employing the Findex dataset is quite similar to our results:[5] New Zealand, Sweden and Finland score at the top, whereas D.R. Congo and Madagascar are placed at the bottom. However, by using aggregate data to quantify "access", the results are similar to macrodata-only indexes such as Sarma (2016) and Sarma and Pais (2011), where Portugal and Spain rank at the top. This result can be explained by the fact that the eigenvectors from PCA are based on the variances of the variables. As aggregate data have a larger variance than the binary ones from the Findex dataset, those have a higher weight when constructing the combined index. In Camara and Tuesta's Table 6, one can notice that weights of "access" are higher than the other dimensions, which explains why their results are similar to a pure aggregate data index, despite adding microdata.

In order to further illustrate these differences, Table 1 compares two countries with a high level of FI in our micro-based ranking (Finland and Sweden) and two countries with high levels of FI in indexes that use macroeconomic variables (Portugal and Spain) for 2011 and 2014.

[5] Full ranking is found in section 6.

Table 1. *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)	2,294.86	2,222.02	3,856.01	4,242.81	2,538.17	2,358.41	2,176.60	1,987.04
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

Source: World Development Indicators and Findex dataset; author’s construction

Portugal displays a higher credit to GDP ratio than Sweden and Finland, even though its population has less access to credit cards and loans from financial institutions. This can reflect that either credit has been mainly designated to firms or that a few individuals hold large amounts of credit. This outcome can also be due to the shrinking of GDP in Portugal and Spain during the Euro crisis – a phenomenon that can distort the results from an index using aggregate data. Similarly, Spain surpassed Sweden in credit card ownership and Finland in formal loans in 2014, but the country lags behind Finland in credit card ownership and Sweden in formal loans, in addition to being slightly behind both countries when it comes to account ownership.

Portugal and Spain also have at least double the number of bank branches than Sweden and Finland. This, however, may not necessarily indicate a higher level of FI as the latter two countries may have highly automatised systems in which individuals can use bank cards to pay in stores or online, thus not needing the physical presence of banks.

In sum, these examples illustrate how aggregated data may provide an inaccurate view of FI, both in HICs and LMICs. We consider that micro-level data is more reliable for creating an index that genuinely reflects the level of FI of individuals in any given country. Therefore, we add to the literature by generating a micro-based index of FI and employing it to assess its socio-economic determinants and its correlates with macroeconomic phenomena.

3. Data

The Global Findex database was launched in 2011 by the World Bank. Further survey rounds were conducted in 2014 and 2017, yielding a pooled cross-sectional database (Demirgüç-Kunt et al. 2018). Using nationally representative data[6] for 149,761, 146,688 and 154,923 different individuals across 2011, 2014 and 2017, respectively, the surveys are constituted mostly of categorical variables (yes or no) that included questions on account and credit card ownership, formal savings and formal credit, as well as different purposes of credit usage. In addition, the dataset also provides information on individuals' characteristics, including gender, age, income quintile and educational level.

Among the 18, 44 and 48 questions used in 2011, 2014 and 2017, we selected the 11 main indicators that correspond to the access, credit and savings dimensions, in line with our definition of FI and the theoretical approaches of more recent studies on FI.[7]

This selection allows us to assess the access of certain financial services, such as an account or card ownerships, and consider usage through loans and savings. Unfortunately, as insurance was only surveyed in 2011, we decided to leave this dimension out of the index as there is no comparative data in subsequent years. Likewise, we cannot select payment information, as it depends on whether the individual made any payment (in cash, kind or electronically), so it does not allow the data to vary. Table 2 presents the selected variables for index construction and their respective dimensions. These indicators are binary variables that take the value of 1 if the survey respondent answered 'yes' to this question and 0 if they answered 'no'.

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[6] Weights are based on household size, sex, age, education and socioeconomic status and are provided by the Findex dataset (Demirgüç-Kunt and Klapper 2013).
[7] Description of indicators can be found in the Appendix (Table A.2).

Table 2. *Variables selected for the multiple correspondence analysis index*

Dimension	Variable
Access	Account at a financial institution[8]
	Debit card ownership
	Credit card ownership
	Mobile money account[9]
Credit	Loan from a financial institution in the past 12 months
	Loan from a store (store credit) in the past 12 months[10]
	Loan to start, operate or expand a farm or business in the past 12 months[11]
	Loan for school fees[12]
	Loan for health purposes
	Loan for housing purposes
Savings	Savings at a financial institution in the past 12 months

For our regression analysis, we also use microdata from the Findex dataset in order to calculate the socio-economic determinants of FI. The available information regards the gender, age, income quintile[13] and educational level of participants. Table 3 shows the summary statistics of those variables.

[8] For 2011, account ownership also includes debit card ownership, which may inflate the values for this year.
[9] For 2011, a new variable was created in order to be comparable to the ones of 2014 and 2017. Further information in the Appendix A.2.
[10] Not available for 2017.
[11] Not available for 2011.
[12] Not available for 2017.
[13] This variable is based on household income quintiles within economies.

Table 3. *Summary statistics of microdata from Findex*

	Data type	Min.	Max.	Mean	Std. Dev.	Observations
FI Index	Continuous	0	100	29.70	10.27	451,363
Female	Binary	0	1	0.54	0.50	451,372
Age	Continuous	15	99	41.30	17.64	449,921
Income quintile	Categorical	1	5	3.20	1.42	451,356
Educational level	Categorical	1	3	1.82	0.68	448,003
In the workforce	Binary	0	1	0.63	0.48	153,923

Note: Employment status is only publicly available for the 2017 wave.

4. Method

4.1 Multiple correspondence analysis

As in Booysen, van der Berg, Burger, Maltitz, and Rand (2008), Pasha (2017) and Tran and Pasquier-Doumer (2019), we employ multiple correspondence analysis (MCA) to construct an index using categorical variables. By imposing fewer constraints on data, MCA is more suitable for analysing discrete or categorical variables than PCA, the more common technique for constructing indexes.

Data-driven weights can be particularly advantageous compared to other techniques, such as the counting approach, in which normative weights are assigned (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 judgment value that may not be considered reasonable (Decancq and Lugo 2013).

The first step in MCA is to recode the data using an indicator matrix of dummy variables (Husson and Josse 2014). An indicator matrix is a table that links individuals and categories. Its elements will be 1, where the category was chosen and 0 otherwise (Greenacre and Blasius 2006). 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, and Yanotti 2018). The assigned weights and coordinates in the plots will then be used to generate the scores for each individual.

4.2 Index construction

MCA generates scores based on standardisation to either rows or columns coordinates (Blasius and 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}:

$$R_{it} = \sum_{h=1}^{J} \frac{Z_{ih} X_{ht}}{a\sqrt{\phi_t}} \qquad (1)$$

where X is the matrix of standard coordinates, a is the number of active variables, and ϕ_t is the eigenvalue of the correspondence analysis on the Burt matrix. However, as we are using principal normalisation, we multiply the row score by the square root of the corresponding principal inertia (eigenvalue), so that

$$R_{it} = \sum_{h=1}^{J} \left(\frac{Z_{ih} X_{ht}}{a\sqrt{\phi_t}}\right) \sqrt{\phi_t} \qquad (2)$$

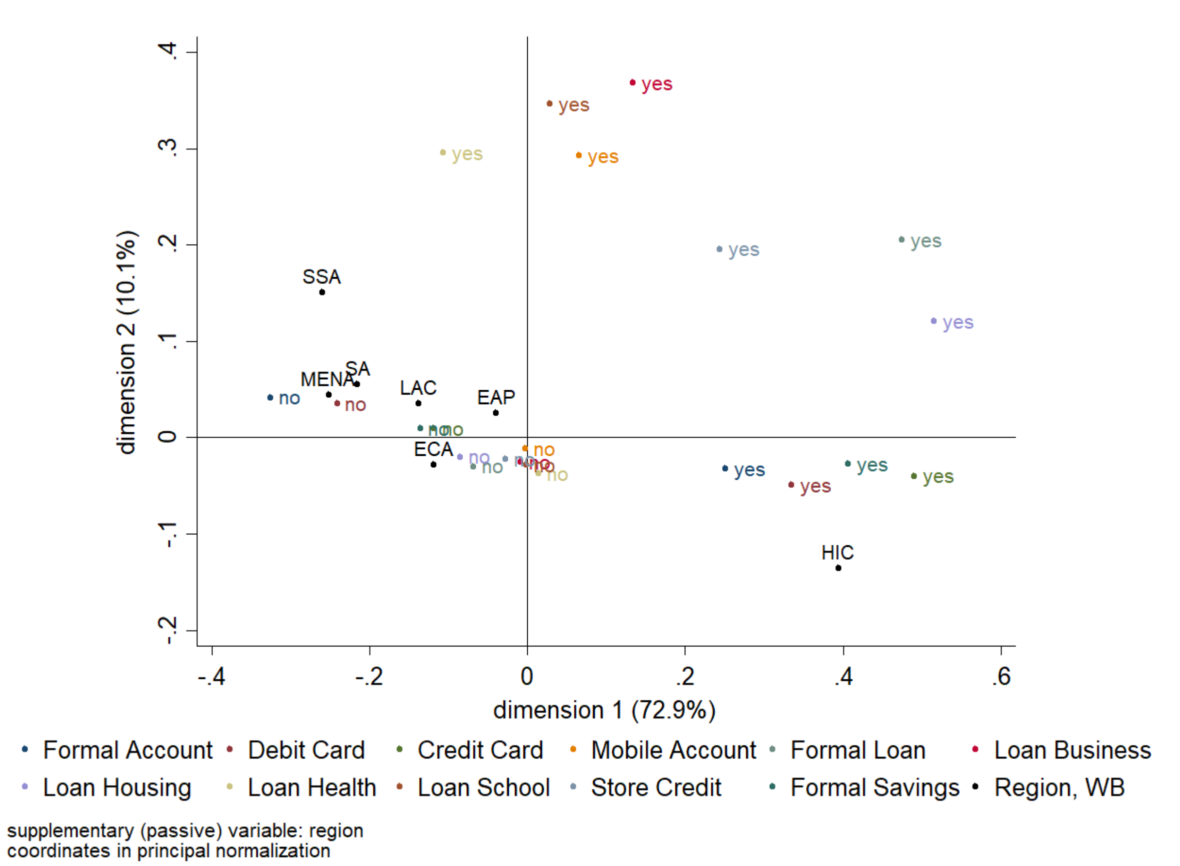
After generating the row profiles for the individuals' scores, we pre-multiply by the category-weights of this first axis.[14] Next, we weigh the results according to the individual's national representation to reach a single value for each individual in the sample for each of the three available years. As in Shimeles and Ncube (2015), the results are then normalised with values between 0 and 1 for inter-temporal and cross-country comparison. Finally, we also multiply the normalised scores by 100 to facilitate interpretation.

4.3 Results

Figure 1 displays the relationship between the selected variables for the years 2011, 2014 and 2017.[15] Using the Euclidean space, MCA allows us to project the answers of 451,372 individuals for each of the indicators. The horizontal axis (dimension 1) is related to formal financial services (account and cards ownership, formal savings, housing loans, and formal loans). The more we move to the right, the more an individual has access to formal financial services. The vertical axis (dimension 2) displays credit relationships and mobile money ownership. Nevertheless, those loans could also be informal, as the dataset does not specify the source of credit. Thus, as presented in the previous section, only the variables that explain the horizontal axis are selected to build our index.

[14] As we demonstrate in Figure 1, the first axis explains a 72.9% variance in the data, and it is related to formal financial services – except for mobile money. Thus, as the strongest dimension that captures the importance of formal financial services, we choose only the first axis to construct the index.
[15] 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.

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



Note: Frequent answers are displayed in the origin and rare responses further apart. The abbreviations correspond to World Bank (WB) 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).

The plot's interpretation of the active variables is straightforward: answers are clustered together if individuals answered yes/no to the same questions. Moreover, frequent answers are placed close to the origin (mean) and rare responses far from it.

Our results show that basic financial services (formal account, debit card, credit card and formal savings) are clustered together at the bottom-right quadrant. This means that individuals tend to use these services jointly. More advanced services, such as store credit, formal loans, and housing loans, are rare and displayed farther from the origin. Likewise, mobile money account and loan for business, health care and school fees are less prevalent and appear at the top of the plot. The plot illustrates that, while certain individuals have access to basic financial services, the majority still have low access to and usage of financial services, as those who have answered ‘no’ to several questions are closer to the origin.

By adding world regions as supplementary variables[16], we are also able to see where world regions are placed based on the information given by their respective sample. For example, individuals in high-income countries (HIC) have access to more formal financial services and are less indebted. On the other hand, individuals from sub-Saharan African (SSA) countries have lower access to and usage of formal financial services and are more indebted. We suggest that this could be related to the fact that the African continent exhibits very low levels of social protection and health care, as these benefits are mostly confined to formal workers, and a high proportion of the workforce is employed in the informal sector (ILO 2017). As a result, those outside the formal sector may need to use other forms of financing medical emergencies, maternity leave or retirement. Likewise, although certain countries, such as Tanzania and Rwanda, have abolished school fees, there are still hidden costs to education, such as uniforms, school supplies and examination fees (Lindsjö 2018; Williams, Abbott, and Mupenzi 2015). Thus, it is plausible that individuals in SSA are more indebted than those in other regions.

In summary, our results indicate that LMICs have lower levels of FI than HICs. This outcome agrees with results in the existing literature (e.g. Demirgüç-Kunt et al. 2018; World Bank 2014). Our analysis also shows that individuals in LMICs are more likely to be indebted to essential social services, particularly health care, which should also be considered when promoting further FI.

[16] 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 ones (Greenacre and Blasius, 2006).

5. Socio-economic determinants of financial inclusion

In this section, we examine key socio-economic determinants of FI: gender, educational level, income, age and employment status. With respect to the relationship between gender and FI, the existing FI literature has two streams. On the one hand, mainstream studies discuss the positive effects of women's access to the formal financial system to provide capital for entrepreneurial activities, thus leading to female empowerment (Bhatia and Singh 2019; Suri and Jack 2016; Velasco and Marconi 2004). Duvendack and Mader's (2019:77) systematic review states that FI effects on women's empowerment are 'positive on the whole, albeit relatively small'. On the other hand, the critical literature highlights the potential harm that FI can cause to women, in particular the effects of over-indebtedness for undertaking debt to use for daily needs, such as food and medicine (Bateman, Duvendack, and Loubere 2019; Guérin 2014; Karim 2011). Finally, empirical studies do not find statistically significant evidence of a relationship between gender and FI or find indirect effects, e.g., as women have lower income and lower levels of education, they are also less likely to use formal financial services (Allen et al. 2016; Aterido, Beck, and Iacovone 2013; Ulwodi and Muriu 2017).

Education, usually addressed as financial literacy, also plays an important role in determining FI. Some studies show that higher literacy levels are correlated with better use of financial services, thus preventing indebtedness (Adetunji and David-West 2019; Lusardi and Tufano 2015). However, there are also findings that financial institutions use complex language and target specific groups, such as the elderly, in order to profit from them (Balliester Reis 2020; Reymão and Oliveira 2017). Thus, understanding how educational levels and FI are related can contribute to designing better policies.

Income, age and employment status are less controversial in the literature as there is a consensus that low-income, elderly and unemployed individuals have less access to and usage of financial services (Demirgüç-Kunt and Klapper 2012a; Fungáčová and Weill 2015; Ulwodi and Muriu 2017; World Bank 2014).

In order to investigate those determinants of FI, we establish the following model, where i corresponds to the individual and t to the year:

$$FI_{it} = \beta_{0t} + \beta_1 female_{it} + \beta_2 educ_{it} + \beta_3 inc_{it} + \beta_4 age_{it} + \beta_5 age_{it}^2 + \beta_6 work_{it} + \beta_7 educ_{it} * female_{it} + \beta_8 inc_{it} * female_{it} + \beta_9 female_{it} * work_{it} + \beta_{10-12} country_{it} + \beta_{13-17} controls_{it} + \varepsilon_{it} \quad (3)$$

The explanatory variables capture the following individuals' socio-economic characteristics: *female* is a dummy variable that takes the value of 0 if male and 1 if female; *age* is a continuous variable representing the individual's age. We add the quadratic term in order to capture a potential non-linear relationship, as we expect that very young and elderly individuals might be less included in the financial system;[17] *educ* is a categorical variable that represents the highest level of education attained by the individual (primary or less, secondary and tertiary or more); and *inc* is the household income quintile within economies in which individuals find themselves (Demirgüç-Kunt et al. 2018). We also include *work* that assumes the value of 1 if the individual is in the workforce and 0 if they are not.[18] Finally, we include three interaction effects: (i) education and gender, (ii) income and gender and (iii) employment and gender. Despite progress, girls and women still have less access to education and employment (Shafiq 2009; United Nations Children's Fund, UN Women, and Plan International 2020) and have

[17] In fact, estimating the model without such quadratic terms display inaccurate results that can be found in Appendix A.3 (Table A.3)
[18] Note, however, that the workforce data is only publicly available in 2017.

lower incomes (World Economic Forum 2021). Thus, we aim to shed further light on how such gender gaps affect financial inclusion.

To account for country-level institutional effects in our model, we include the mean by country and year of GDP per capita (in logs), population size (in logs) and rule-of-law. We transform the first two variables in logs to facilitate the interpretation, whereas the rule-of-law variable ranges from -2.5 to 2.5 and cannot be transformed in that manner. Finally, we add control variables using aggregate information to account for further characteristics that might influence the level of FI, namely: ATMs per 100,000 adults, bank branches per 100,000 adults, rural population (as a percentage of the total population), and unemployment rate.

As our sample consists of different individuals in each wave, we use a repeated cross-section with contemporaneous explanatory variables.[19] Based on the existing literature, we do not expect endogeneity to be a significant problem in our model, so that the Ordinary Least Squares (OLS) estimator is the most efficient one under the Gauss Markov assumptions. Nevertheless, we do identify heteroskedasticity using a White test. We correct for it using clustered standard errors by country.

In order to test if the results from individuals in HICs and LMICs[20] follow the same regression function, we performed a Chow test in the pooled version of the model. The test shows whether explanatory variables have different impacts on each of the two groups in the sample. The null hypothesis is that there are no differences between groups. The test statistic is 721.62, which is statistically significant at the 1% level.[21] This suggests that there are differences between individuals in these two regions. We also further disaggregate by geographical region to detect potential differences within LMICs, and we notice key differences among regions as shown in

[19] As the survey is not a panel dataset, a within estimator is not feasible.
[20] Denomination provided by the World Bank and might change over time.
[21] The critical value of the F-distribution is 1.85.

sub-section 5.2. Finally, note that certain variables might not be included in each wave as reported in Table 2 so that an interpretation of time effects should be conducted carefully.

5.1 LMICs vs HICs

Accordingly, we estimate the above equation for 451,372 individuals and, to account for the heterogeneity in slope coefficients[22], we estimate FI for LMICs and HICs separately (Table 4).[23]

[22] The results for the full sample can be found in the Appendix A.3 (Table A.4)
[23] We consider our results to be robust, as different robustness checks have shown that coefficients will remain very similar. Such check can be found in Appendix A.3.

Table 4. *Determinants of financial inclusion by developing vs developed countries (1)-(3): LMICs; (4)-(6): HICs.*

	(1) 2011	(2) 2014	(3) 2017	(4) 2011	(5) 2014	(6) 2017
female	-0.15	-0.09	0.95***	-2.87***	-0.79**	-0.48
	(0.13)	(0.19)	(0.29)	(0.57)	(0.39)	(0.40)
1.educ	.	.	.	.	.	.
2.educ	1.16***	2.32***	2.94***	0.53	1.42***	0.47
	(0.12)	(0.20)	(0.24)	(0.56)	(0.52)	(0.66)
3.educ	2.29***	4.27***	5.14***	-1.01	1.23	-0.13
	(0.19)	(0.24)	(0.26)	(0.87)	(0.75)	(0.86)
1.inc	.	.	.	.	.	.
2.inc	0.45***	0.78***	0.71***	0.78***	0.55**	0.94***
	(0.08)	(0.12)	(0.14)	(0.23)	(0.23)	(0.23)
3.inc	0.78***	1.45***	1.78***	0.82**	1.00***	1.50***
	(0.08)	(0.13)	(0.15)	(0.34)	(0.21)	(0.25)
4.inc	1.27***	2.30***	2.58***	0.89**	1.44***	1.51***
	(0.10)	(0.15)	(0.17)	(0.43)	(0.23)	(0.26)
5.inc	1.83***	3.15***	3.51***	-0.36	1.09***	1.71***
	(0.11)	(0.17)	(0.22)	(0.42)	(0.26)	(0.31)
work	.	.	1.90***	.	.	2.75***
			(0.17)			(0.24)
fem*educ1	.	.	.	.	.	.
fem*educ2	0.02	-0.10	-0.52***	0.63	0.31	0.42
	(0.08)	(0.14)	(0.18)	(0.43)	(0.35)	(0.39)
fem*educ3	-0.12	-0.34	-0.98***	0.78	0.34	0.87*
	(0.14)	(0.21)	(0.26)	(0.51)	(0.38)	(0.46)
fem*inc1	.	.	.	.	.	.
fem*inc2	-0.11	-0.20	-0.27**	-0.31	0.07	-0.26
	(0.10)	(0.13)	(0.12)	(0.30)	(0.31)	(0.23)
fem*inc3	-0.18*	-0.17	-0.80***	-0.44	-0.11	-0.09
	(0.09)	(0.14)	(0.16)	(0.33)	(0.27)	(0.26)
fem*inc4	-0.31***	-0.45***	-0.88***	-0.58	-0.30	-0.12
	(0.09)	(0.13)	(0.18)	(0.39)	(0.27)	(0.23)
fem*inc5	-0.44***	-0.54***	-0.98***	0.06	-0.21	-0.25
	(0.10)	(0.14)	(0.23)	(0.43)	(0.27)	(0.27)
fem*work	.	.	-0.11	.	.	-0.60**
			(0.17)			(0.26)
age	0.15***	0.29***	0.26***	0.36***	0.36***	0.35***
	(0.01)	(0.01)	(0.02)	(0.05)	(0.03)	(0.03)
age2	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lgdppcavg	0.62***	1.02***	0.77*	-0.06	1.37**	1.46**
	(0.17)	(0.32)	(0.40)	(0.69)	(0.60)	(0.65)
lpopavg	-0.03	0.20*	0.25*	-0.32**	0.00	0.14
	(0.05)	(0.11)	(0.13)	(0.13)	(0.13)	(0.14)
ruleavg	0.41**	0.78***	0.97***	4.34***	1.90***	2.90***
	(0.16)	(0.23)	(0.32)	(0.68)	(0.36)	(0.50)
ATMs	0.01	0.02***	0.02***	0.01***	0.01**	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
branch	0.01	0.01	0.01	-0.00	-0.01	0.00
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
rural	0.02***	0.03**	0.03*	0.01	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
unemp	-0.02	-0.03	0.00	-0.01	0.04	0.02
	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)
Constant	7.25***	12.36***	8.29*	19.40***	15.09**	7.64
	(1.53)	(3.68)	(4.58)	(5.40)	(6.28)	(7.10)
Observations	96,727	89,704	85,557	37,041	40,650	39,149
R-squared	0.16	0.21	0.22	0.16	0.17	0.19

***statistically significant at the 1% level; ** at the 5% level; * at the 10% level using the t-test

Note: Clustered standard errors in parentheses. The financial inclusion dependent variable ranges from 0 to 100.

Our first finding is that gender by itself does not seem to play an important role in determining FI in LMICs. In contrast, *female* does present a statistically significant negative coefficient in HICs in 2011 and 2014. In fact, the variable has a positive coefficient in 2017 in LMICs, showing that the existing research confirming such gender gap might be biased (e.g. Demirgüç-Kunt et al., 2013; Fungáčová and Weill, 2015). Such conclusions are possibly due to the lack of interaction effects between gender and education, income and employment status. In turn, our interaction effects display an interesting finding: whereas education and income play a key role in determining the level of FI in LMICs, women with higher incomes and higher levels of education in LMICs are less included than poorer and less formally educated women. Based on our results, a woman with tertiary education from a LMIC in 2017 has, on average, 5.11 percentage points (p.p.) higher FI level than a man with primary education. Moreover, a woman in the richest 20% quintile has a 3.48 p.p. higher score in the FI index than a man in the bottom 20% quintile. Whereas such effects might seem small, our index of FI ranges from 0 to 100, with the 25-75 percentiles concentrating those individuals with 20.17 to 36.92 points on average. In 2017, for example, the mean FI level was 31.39 with a standard deviation of 6.93, as shown by Table 5. Thus, a 5.11 p.p. change constitutes an economically significant difference.

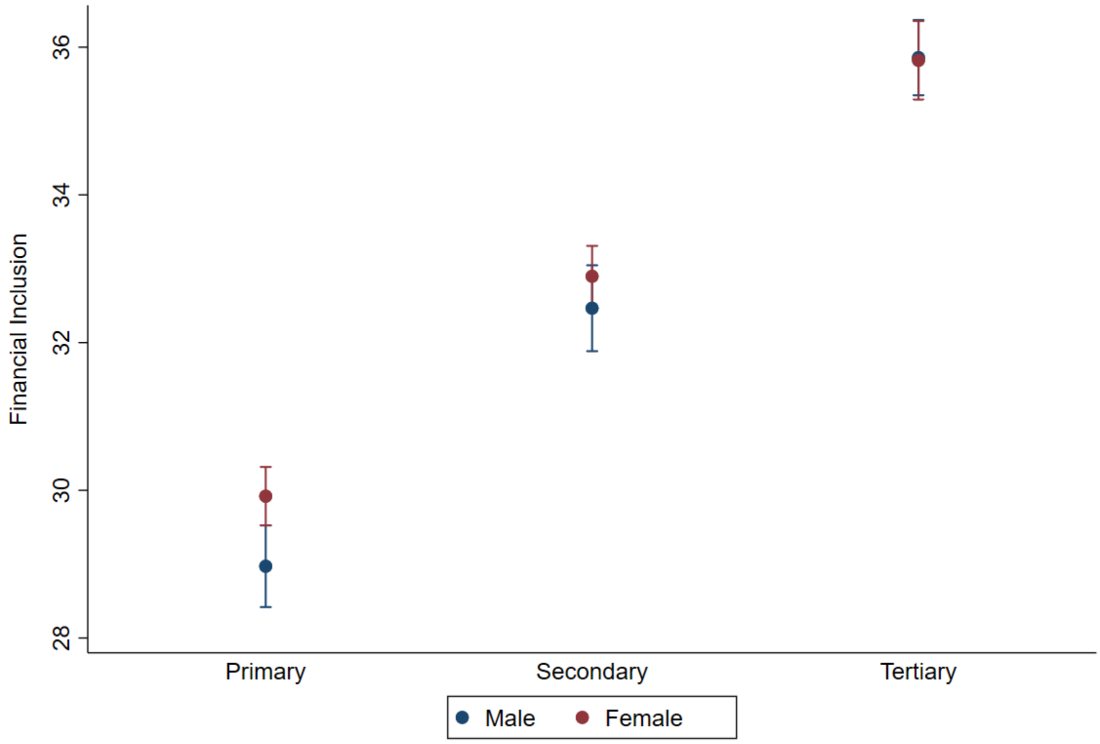
Table 5. *Summary statistics of the financial inclusion index, low- and middle-income countries and high-income countries*

	LMICs			HICs		
	2011	2014	2017	2011	2014	2017
Mean	17.48	34.27	31.39	24.38	40.72	39.09
St. dev.	3.80	5.94	6.93	8.40	6.73	7.59
Percentile						
1%	10.38	19.81	13.89	10.23	24.21	20.64
25%	15.30	31.10	27.80	19.28	37.36	34.95
75%	18.80	37.35	34.88	27.45	43.29	42.17
99%	30.68	52.23	51.66	54.82	63.44	63.94
Observations	108,976	101,021	111,248	40,776	45,667	43,675

Note: The financial inclusion index ranges from 0 to 100

We can visualise the gender gap in Figure 2, where we predict the marginal effects of gender with respect to education in LMICs for 2011, 2014 and 2017. We notice that, in LMICs, women with primary education or less have greater FI levels than men. This gap is reduced for those individuals with secondary education and is virtually zero for men and women with higher education.

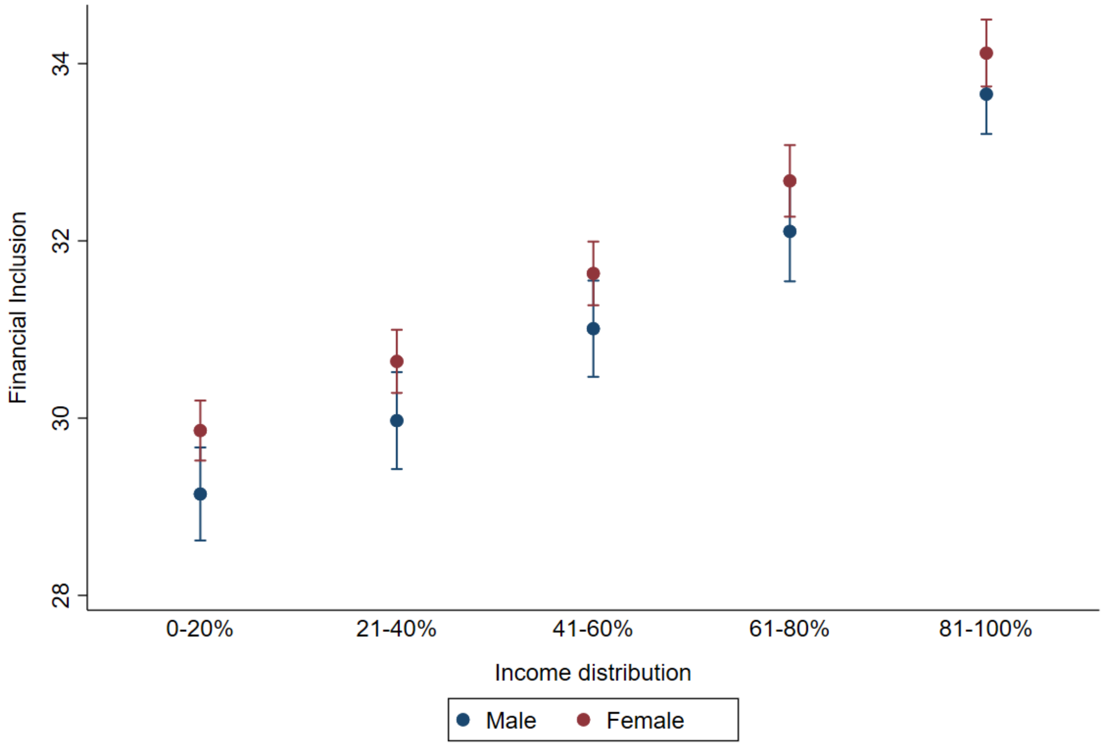
Figure 2. *Financial inclusion by educational level and gender in LMICs (pooled version)*



Note: Other explanatory variables were held at the mean. We use the 95% confidence interval.

The situation is even more surprising when income is considered. Figure 3 displays that, regardless of income level, women present higher levels of FI than men in LMICs. Whereas there is a slight reduction of such gap for richer individuals, women still have higher FI levels.

Figure 3. *Financial inclusion by income quintile and gender in LMICs (pooled version)*



Note: Other explanatory variables were held at the mean. We use the 95% confidence interval. The range runs from the poorest 0-20% to the richest 81-100%.

Such findings are the opposite in HICs, where education and income play a minor role in determining FI, but gender has a more substantial negative effect. In those countries, women have, on average, lower levels of FI despite their educational level or income quintile.

Employment also displays a significant effect on FI. Whereas the interaction term between gender and employment is not statistically significant in LMICs, we notice that workers have, on average, higher levels of FI than those out of the workforce. In turn, in HICs, women in the workforce do display slightly lower FI levels than men but still are 1.67 p.p. more included than unemployed men.

Concerning age, our finding is also somewhat surprising as it shows that FI drops at a later age in LMICs. In HICs, FI increases up to 40, 44 and 46 years old in 2011, 2014 and 2017. In LMICs, in turn, FI peaks at 47, 50 and 55 years, dropping after that.

Our institutional effects also display interesting results. We notice that individuals that reside in countries with higher GDP per capita present higher levels of FI in both HICs and LMICs. Population, in contrast, does not seem to have a consistent impact. Finally, rule-of-law does have a statistically significant effect on FI in all specifications, albeit such effect is stronger in HICs.

Finally, our control variables do not seem to be relevant for individuals' FI levels. For example, a 1% increase in ATMs per 100,000 individuals only increases FI by 0.0002 p.p. in LMICs in 2014 and 2017, whereas bank branches and unemployment levels do not affect the individual-level FI. Rural population, in turn, displays unexpected results as it has a small but positive effect on FI for those individuals living in LMICs. However, without further information, it is not possible to hypothesise the reasons behind such an effect.

Our findings have three important implications. First, they challenge the hypothesis that gender by itself is an essential determinant of FI and a significant factor for the successful implementation of FI to reduce poverty, in particular in LMICs (Demirgüç-Kunt et al. 2013; Ghosh and Vinod 2017; Johnson and Nino-Zarazua 2011; Swamy 2014). Second, educational level and income display a greater impact in determining FI than gender. This finding is in line with existing econometric studies (e.g. Allen et al. 2016; Aterido et al. 2013; Ulwodi and Muriu 2017) that conclude that the FI gender gap may be associated with other types of gender disparities, such as lower education, lower income and a lower likelihood of being formally employed. Finally, as we notice in Table 6, there is a positive correlation of 25.41% between education and income, so that similar trends of their effects on FI are not surprising.

Table 6. *Participant's educational level by income quintile, pooled*

	Income quintile					
Education	Poorest 20%	Second 20%	Middle 20%	Fourth 20%	Richest 20%	Total
Primary	31,048	29,280	27,997	25,716	21,876	135,917
Secondary	19,930	24,201	28,846	34,116	42,445	149,538
Tertiary	2,285	3,013	4,551	7,260	16,425	33,534

Finally, we notice that gender disparities in terms of FI are stronger in HICs. This result also challenges the current focus on closing the FI gender gap in LMICs and suggests that other policies, such as employment and education for girls and women, should be considered if policymakers are to promote FI.

5.2 Geographical regions

Another way to identify differences is to investigate the determinants of FI by geographical regions. Table 7 displays a pooled cross-section analysis where we distinguish six sub-samples of LMICs: East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), Middle East and North Africa (MNA), South Asia (SAS) and Sub-Saharan Africa (SSA).

Table 7. *Determinants of financial inclusion by geographic region of LMICs*

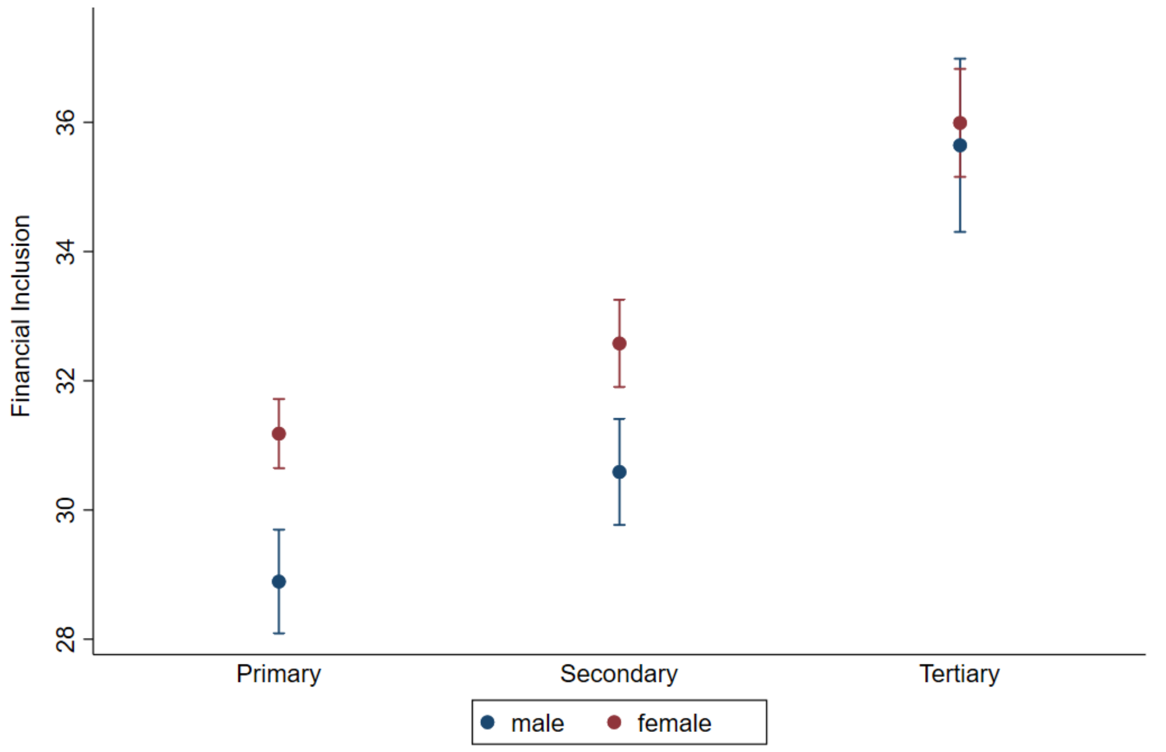
	(1) EAP	(2) ECA	(3) LAC	(4) MNA	(5) SAS	(6) SSA
female	0.64	0.54	0.58**	-0.91	-0.41*	-0.14
	(0.51)	(0.86)	(0.22)	(0.60)	(0.18)	(0.24)
1.educ	.	.	.	.	.	.
2.educ	2.00***	2.86***	1.51***	1.91***	1.67***	2.79***
	(0.37)	(0.67)	(0.18)	(0.33)	(0.29)	(0.17)
3.educ	4.55***	4.29***	4.80***	3.29***	2.76***	4.51***
	(0.39)	(0.66)	(0.36)	(0.44)	(0.45)	(0.35)
1.inc	.	.	.	.	.	.
2.inc	0.79**	0.86***	0.54**	0.55**	0.58**	0.62***
	(0.26)	(0.15)	(0.21)	(0.21)	(0.23)	(0.11)
3.inc	1.39***	1.56***	1.76***	1.28***	0.79**	1.24***
	(0.32)	(0.15)	(0.24)	(0.33)	(0.24)	(0.14)
4.inc	2.20***	1.84***	2.77***	2.03***	1.37***	1.95***
	(0.49)	(0.19)	(0.26)	(0.38)	(0.23)	(0.15)
5.inc	2.61***	2.39***	3.81***	2.82***	2.16***	2.81***
	(0.43)	(0.20)	(0.30)	(0.52)	(0.21)	(0.20)
fem*educ1	.	.	.	.	.	.
fem*educ2	-0.48	-0.41	-0.29**	0.03	-0.25**	0.15
	(0.34)	(0.72)	(0.13)	(0.33)	(0.09)	(0.15)
fem*educ3	-1.05**	-0.55	-1.27***	0.70	0.05	0.22
	(0.43)	(0.77)	(0.28)	(0.39)	(0.54)	(0.24)
fem*inc1	.	.	.	.	.	.
fem*inc2	-0.22	-0.32*	-0.02	-0.18	-0.36*	-0.16
	(0.25)	(0.16)	(0.18)	(0.22)	(0.16)	(0.11)
fem*inc3	-0.39	-0.61***	-0.64**	-0.46	-0.14	-0.12
	(0.28)	(0.21)	(0.23)	(0.31)	(0.15)	(0.12)
fem*inc4	-0.58**	-0.46***	-1.02***	-0.60	-0.32	-0.23*
	(0.25)	(0.15)	(0.24)	(0.40)	(0.17)	(0.12)
fem*inc5	-0.50	-0.69***	-1.16***	-0.70	-0.42**	-0.38**
	(0.28)	(0.22)	(0.26)	(0.58)	(0.14)	(0.17)
age	0.26***	0.25***	0.25***	0.30***	0.29***	0.18***
	(0.04)	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)
age2	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lgdppcavg	2.81*	0.83**	0.57*	-0.44	-0.23	0.46*
	(1.40)	(0.38)	(0.32)	(0.67)	(0.59)	(0.27)
lpopavg	-0.04	0.27	-0.32*	0.13	0.17***	0.07
	(0.25)	(0.17)	(0.16)	(0.35)	(0.04)	(0.06)
ruleavg	-1.53*	0.44	-0.03	-0.97**	-0.93*	0.49**
	(0.68)	(0.58)	(0.24)	(0.42)	(0.42)	(0.21)
ATMs	0.03**	-0.00	0.02**	0.10***	0.20**	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.07)	(0.01)
branch	0.03	-0.01	0.05***	-0.03	0.08	0.06
	(0.02)	(0.01)	(0.02)	(0.03)	(0.10)	(0.07)
rural	0.04	-0.05*	-0.01	-0.03	0.08**	0.03**
	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)
unemp	0.05	0.08***	0.14***	0.05	0.01	-0.07***
	(0.22)	(0.02)	(0.05)	(0.04)	(0.03)	(0.02)
2014	17.07***	17.38***	17.30***	16.03***	15.93***	16.04***
	(0.39)	(0.29)	(0.15)	(0.30)	(0.39)	(0.19)
2017	14.05***	15.43***	13.76***	12.51***	12.69***	13.08***
	(0.67)	(0.39)	(0.21)	(0.54)	(0.48)	(0.18)
Constant	-15.88	-1.35	7.38*	8.44*	-0.49	4.12
	(12.53)	(4.80)	(4.02)	(3.95)	(5.40)	(3.17)
Observations	33,656	53,930	45,443	28,161	25,230	76,589
R-squared	0.64	0.71	0.70	0.69	0.75	0.75

***statistically significant at the 1% level; ** at the 5% level; * at the 10% level using the t-test

Note: Clustered standard errors in parentheses. The financial inclusion variable ranges from 0 to 100.

Table 7 shows us that, in fact, there are striking differences between regions. EAP (including China), ECA and LAC display results similar to the aggregate result for LMICs: where women do not display lower FI levels, the gender gap does shrink among the richer and more educated individuals. However, the gender gap for those with lower education and income levels is positive, i.e., women display higher levels of FI. This means that women do not seem to have less access to and usage of financial services, contrary to some of the existing findings. Figure 4 displays the results for LAC with respect to gender and education to demonstrate this outcome.

Figure 4. *Financial inclusion by education and gender in Latin America and the Caribbean (pooled version)*



Note: Other explanatory variables were held at the mean. We use the 95% confidence interval.

For example, a woman in LAC with tertiary education, on average, has a FI level of 4.11 p.p. higher than a man with only primary education. In turn, in SAS (which includes Afghanistan, Bangladesh and India), education and income play a slightly less key role in comparison to gender. However, a woman in the top 20% of the income distribution would still have a 1.33 p.p. higher level of FI than a man at the poorer quintile. Finally, MNA and SSA results show that, whereas there is a small negative effect of gender on FI, more educated women do present higher FI levels. For instance, a woman with tertiary education in an MNA country has, on average, a FI level of 3.08 p.p. greater than a man with primary education.

As in the previous analysis, the effect of age is quite different over regions, with the level of FI declining in SAS and EAP at around 46 years old, ECA at 49, LAC at 52, and MNA and SSA at 54 years old.

Country-level institutional effects are also diverse. Within EAP countries, 1% change in GDP per capita determines 0.028 p.p. of FI at the individual level, whereas such effect is more minor or inexistent within other regions. Population also plays different roles depending on the region, positively contributing to FI levels in ECA and SAS but reducing it in LAC. Finally, rule-of-law has an unexpected sign in our results. Most specifications display a negative effect on FI, i.e., that individuals living in countries with higher rule-of-law scores present lower levels of FI. Nonetheless, further investigation must be conducted in order to explain such a result.

As in the previous analysis, control variables also do not seem to affect FI as much as education and income. A percentage increase in the number of ATMs in SAS also just contributes at 0.002 p.p. of FI. Finally, a percentage increase in unemployment in LAC, raises individual-level FI by 0.014 p.p. Thus, as in our general LMICs results, we notice that aggregate variables have less impact on individual-level FI than socio-economic determinants.

5.3 The role of education, income and informality

In Table 4, we saw that education and income level had a much stronger effect in determining FI in LMICs than HICs. The level of labour market informality could explain such different impacts in developing regions. Being in the formal labour market may require a bank account to receive wages, as well as possibly enough income for savings, as employers must follow minimum wage regulations.[24] Moreover, providing workers with a regular income stream increases the potential for loans and instalment payments, as they are considered more creditworthy by financial institutions.[25]

In LMICs, higher educational levels are linked to employment in the formal labour market, which also leads to higher earnings. According to the ILO (2018), 93.9% of individuals with no education in LMICs were informal workers. These numbers drop drastically for individuals with secondary (59.1%) and tertiary education (32%), but not as much for those with only primary schooling (86%). In HICs, in contrast, 52.7% of individuals with no education were in the informal labour market,[26] and the gap between informal workers with primary (40.5%), secondary (19.2%) and tertiary education (16.1%) is much narrower. The report also shows that poverty rates are higher among those in the informal labour market. In Zambia, for instance, 79.3% of informal workers earn less than US$3.10 a day, in comparison to only 14.7% of workers in the formal economy.

In our econometric analysis, whereas an employed woman in a LMIC and HIC has, respectively, a 2.74 p.p. and 1.67 p.p. higher level of FI than an unemployed man in 2017, we are unable to disaggregate if this individual is working on the formal or informal labour market.

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[24] In 2015, 90% of the 186 ILO members had implemented the minimum wage (ILO 2016:5–6)
[25] The relationship between regular income streams and FI can be found Lavinas (2018).
[26] This average is boosted by high-income Asian and Pacific countries. In Europe and Central Asia this number falls to around 30%.

While more detailed information on employment status information is not publicly available on the Findex dataset, other studies have found evidence that supports the hypothesis that informality is a key determinant of FI. According to Demirgüç-Kunt et al. (2013), self-employed and unemployed workers have a lower likelihood of having a bank account, formal savings, and credit than employed workers. Similarly, Allen et al. (2016) find that employed individuals are more likely to own and use a bank account. Thus, we suggest that higher levels of FI based on education and income in LMICs may be related to the rate of labour market formality.

In a nutshell, our econometric results show that although gender does not exhibit strong economic significance, women with higher income and education levels do display higher FI levels in LMICs. We suggest that these variables may be linked to employment status, as individuals in the formal labour market are more likely to need a bank account and earn higher wages, thus being more likely to use other financial services, such as savings and loans for housing. Thus, our results confirm the outcomes of other empirical studies that a FI gender gap is associated with other types of gender disparities, such as lower education, lower income and a lower likelihood of being formally employed (Allen et al. 2016; Aterido et al. 2013; Ulwodi and Muriu 2017).

6. Global Ranking of Financial Inclusion

The second contribution of this article is the creation of a country ranking of FI, a standard method of comparing the level of FI across countries (Amidžić et al. 2014; Camara and Tuesta 2014; Honohan 2008; Sarma 2016). However, considering the limitations of such an index using aggregate variables, we use solely micro-level data from the Findex dataset. This section presents the ranking and compares it to two existing global rankings of FI: Sarma's (2016) and Camara and Tuesta's (2014) indexes.

6.1 Construction of the ranking

In order to construct the ranking, we use the previously generated normalised micro-level index and calculate the simple average over all the individuals of the respective country (Table 8). Such micro-based country-level ranking displays a more accurate picture of the individual-level access and usage of formal financial services, allowing us to compare FI levels across countries and years.

Table 8. *The Global Ranking of Financial Inclusion (GRFI)*

Rank	GRFI 2011	Score	GRFI 2014	Score	GRFI 2017	Score
1	Sweden	1.000	Norway	1.000	Norway	1.000
2	New Zealand	0.961	New Zealand	0.948	Canada	0.939
3	Finland	0.943	Canada	0.933	New Zealand	0.881
4	Australia	0.935	Sweden	0.920	Sweden	0.881
5	Canada	0.920	Finland	0.890	Luxembourg	0.865
…						
50	China	0.381	Macedonia, FYR	0.442	Chile	0.449
51	Brazil	0.361	Saudi Arabia	0.441	Bulgaria	0.438
52	Saudi Arabia	0.360	Greece	0.441	Hungary	0.436
53	Serbia	0.357	Jamaica	0.432	Venezuela, RB	0.425
54	South Africa	0.351	Serbia	0.430	Uruguay	0.423
…						
140	Madagascar	0.013	Burundi	0.022	Afghanistan	0.021
141	Burundi	0.011	Madagascar	0.019	South Sudan	0.011
142	Guinea	0.010	Niger	0.000	Chad	0.008
143	Congo, Dem. Rep.	0.006			Madagascar	0.006
144	Niger	0.000			Niger	0.000

Note: The ranking is the country-level normalised results of the multiple correspondence analysis microdata index. The full ranking is found in Appendix A.4 (Table A.6).

As we notice, Nordic countries, such as Norway and Sweden, are found at the top. These are closely followed by other HICs, such as Canada and New Zealand. In the middle of the ranking, we still find HICs, such as Chile and Greece, but also middle-income countries, as Brazil and South Africa. Finally, low-income countries often hold lower FI levels. Such outcome leads to the hypothesis of a correlation between FI, income level and distribution.

Whereas HICs have, in general, higher levels of FI, we do find that some of those countries display FI characteristics closer to LMICs, in particular Greece, Italy, Poland, Saudi Arabia and Chile. Greece is the strongest outlier, as it drops from position 44th to 52nd to 57th over time. In turn, Italy and Poland have an upward trend, starting lower than Greece in 2011, but rising to positions 28th and 35th in 2017, respectively. Saudi Arabia's position also declined over the years, going from 52nd in 2011 to 55th in 2017. Although this is not such a significant drop, the country is still surpassed by several LMICs, including Venezuela, Thailand, and Turkey. Finally, Chile shows an upward trend through the ranks.[27] The country's FI level rose from position 62nd to 48th but declined to 50th in 2017. Such outcome is more similar to other upper middle-income countries than with HICs in general, as Chile is often surpassed by China, Malaysia and Mauritius, among others.

A surprising finding regards LMICs that have had strong microfinance programmes in the past decade but still display low levels of FI. Tanzania, for instance, implemented a National Framework for Financial Inclusion in 2014 and has seen a rise in mobile money accounts and digital credit (Kaffenberger and Totolo 2018; Lotto 2018; National Financial Inclusion Council 2017). However, the country displays very poor results over time. The country is placed in 107th in 2011, dropping to 113th in 2014 and further to 129th in 2017.

[27] Chile was only considered a HIC after 2013.

Another interesting case is India, a country with solid policies pro-microfinance and FI (Bateman 2012; Chakravarty and Pal 2013; Chandrasekhar and Ghosh 2018; Duflo et al. 2013; Guérin, D'Espallier, and Venkatasubramanian 2013). Despite rising through the ranks from position 93rd in 2011 to 70th in 2014, such outcome is below other LMICs, such as China, Brazil and the Russian Federation. Whereas such results are surprising and deserve further investigation, a more detailed comparative analysis is beyond the scope of this article.

6.2 Comparison to existing rankings

The GRFI provides a new perspective on FI. As argued above, if the purpose of FI is to include individuals, aggregate variables that have been used to construct previous indexes may not be suitable. Comparing our results to Sarma's (2016), which is the most complete ranking using only macroeconomic variables, and Camara and Tuesta's (2014), who mix macro and micro-level data, we find striking differences.[28] Table 9 compares the top 10 countries in the three indexes.

[28] Sarma (2016) has data for 2004-2014 and Camara and Tuesta (2014) only for 2011. Variables used in the indexes of such studies can be found in Table A.1 of the Appendix.

Table 9. *Ranking comparison*

Year	2011			2014	
Rank	GRFI	Sarma (2016)	Camara and Tuesta (2014)	GRFI	Sarma (2016)
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

A key issue to note when analysing those results is that the highest-ranked countries in our GRFI, such as Sweden and New Zealand, are not included in Sarma (2016). Other countries with important financial centres, such as the United States, Luxemburg or Singapore, are also not present in Sarma's ranking.[29] Second, by selecting aggregate variables to analyse individuals' FI, results are inflated for several countries, particularly Portugal and Spain, both in Sarma (2016) and Camara and Tuesta (2014). As GDP in those countries has contracted during the Euro crisis, their credit to GDP ratios has increased, thus boosting their index values. Moreover, as we discussed in Section 2, those countries have a very high number of bank branches and ATMs, increasing their position at the ranking. Furthermore, as we saw in Section 5, those aggregate variables do not play a key role in determining individual-level FI.

[29] The top financial hubs were London, New York, Hong Kong and Singapore in 2011 and 2014 according to the Global Financial Centres Index.

Our results are very similar to the first stage of Camara and Tuesta's (2014) ranking, as the study uses the 2011 World Bank Findex data in order to construct the index. In it, the top countries are New Zealand, Sweden and Finland. Nonetheless, in the second stage, the study includes aggregate variables, generating a final ranking similar to Sarma's (2016).[30] Thus, as we notice in Table 9, Portugal and Spain rank in the top 3, whereas Sweden and Finland are placed in 16th and 19th. Therefore, we conclude that while aggregate variables are a good indication of the level of financial development, they do not represent well a country's level of FI.

In order to assess the difference between our index and Sarma's (2016)[31], we conduct the Spearman's rank correlation (*rho*) and Kendall's rank correlation (*tau*) tests. Sarma's index and the GRFI have 101 countries in common in 2011 and 86 countries in 2014. For 2011, the tests displayed a Spearman's rho of 0.84 and Kendall's tau of 0.64, both significant at the 1% level. For 2014, the result was a rho of 0.74 and tau of 0.54, both also significant at the 1% level.

These results suggest that, whereas we find a positive and sometimes strong correlation between the two indexes, there are still significant differences. Both indexes display HICs are ranked higher than LMICs, in general, for 2011 and 2014. Nonetheless, the variable selection leads to a different order within each ranking. Therefore, while FD and FI might be correlated, they do not represent the same phenomenon.

In sum, we notice that an index of FI using only individual-level data displays very different results of those using either aggregate information or a mix of both. This occurs as aggregate data inflate the scores of countries with low-technology financial systems and those undergoing

[30] A comparison to Aslan et al. (2017) would be more appropriate, as the study also selects variables from the Findex dataset. Yet, the paper does not provide the scores for FI, nor rank countries.
[31] Comparing the GRFI with Camara and Tuesta's (2014) is not possible as the study does not provide the actual values of each country.

an economic crisis, whereas it penalises countries with lower debt levels. Therefore, while aggregate information may be useful to measure financial development, we confirm that individual-level data is more accurate in providing the level of financial inclusion in a country.

6.3 The application of the GRFI

To test whether our GRFI is also useful for a macro-economic assessment, we assess its correlation with three aggregate variables: GDP per capita, income inequality measured by the Gini coefficient, and the self-employment rate in the labour market as a proxy for informal work. Based on the available literature, we expect GDP to positively correlate to the GRFI, while the Gini coefficient will have a negative one (Demirgüç-Kunt, Klapper, and Singer 2017; Karpowicz 2016; Park and Mercado 2018; Sethi and Acharya 2018; World Bank 2014). Moreover, we expect the relationship between self-employment and FI to be negative, as individuals in the informal labour market may not need or use the formal financial system.

First, Table 10 shows a strong positive correlation between a country's income level, measured by GDP per capita (GDPPC)[32], and the level of FI of individuals of that country, reaching 0.874 in 2017. Our test of equality of correlation for 2011 and 2014 is rejected at the 5% value (p-value=0.03), suggesting there is indeed a statistically significant increase of the correlations over time. However, the correlation between GDPPC and our index is not statistically different from 2014 to 2017 (p=0.33), indicating a stabilisation of such correlates. This finding suggests a robust connection between income and access to and usage of financial services, which could explain why HICs are mainly at the top of the ranking while LMICs are placed at the bottom.

[32] in PPP current international US$.

Table 10. *Pearson correlation of GRFI and GDP per capita, Gini coefficient and self-employment*

GRFI	2011	Obs.	2014	Obs.	2017	Obs.
GDPPC	0.745	139	0.843	137	0.874	140
GINI	-0.466	73	-0.371	75	-0.457	66
SELF	-0.687	140	-0.769	138	-0.762	141

Source: World Development Indicators, World Bank

Second, the comparison shows that income inequality, measured by the Gini coefficient, has a less meaningful relationship but still somewhat significant. Income inequality has a negative correlation with our ranking, which is expected given other studies' results, at a level of -0.466 in 2011, -0.371 in 2014 and -0.457 in 2017. In this case, the test of equality of the correlation from 2011 to 2014 (p=0.49) and from 2014 to 2017 (p=0.54) shows that there is no statistically significant difference throughout time, so that these fluctuations are due to changes in sample size. This result could partly elucidate why countries with higher Gini coefficients such as Sweden (Gini of 27.6 and 28.4 in 2011 and 2014, respectively) and Finland (27.6 and 26.8, respectively) are found at the top of the GRFI ranking, while those with higher levels of income inequality, such as Niger (31.5 and 34.3) and El Salvador (42.3 and 41.6), are found at the bottom.

Third, self-employment rates display a high negative correlation with the GRFI, ranging from -0.687 in 2011 to -0.762 in 2017. Moreover, we fail to reject our test of correlation coefficient equality, indicating a stable relationship between self-employment and FI. We consider that the strong correlation backs up our hypothesis that there is a negative relationship between labour market informality and FI. Countries with high levels of self-employment, such as Niger (94.96% in 2017) and D.R. Congo (79.98% in 2017), present lower levels of FI. We consider that this relationship lies in the fact that those out of the formal labour market may not need a bank account for receiving wages and may be more likely to have formal loans refused. Moreover, earning less income reduces the likelihood of savings and insurance.

In summary, we observe that the aggregation of individual-level data of the Findex is indeed a valuable tool for assessing the relationship between FI and macroeconomic variables. Without inferring causality, these last findings indicate that countries with higher income, less income inequality, and lower self-employment tend to have higher levels of FI.

7. Conclusion

This article developed a new index of financial inclusion exclusively using micro-level information. Employing multiple correspondence analysis, we generated index scores for 451,372 individuals in about 150 countries for 2011, 2014 and 2017 using the World Bank's Findex dataset. The scores were then used to estimate the socio-economic determinants of financial inclusion. Furthermore, the index was used to construct a Global Ranking of Financial Inclusion, allowing for an over-time and a cross-country comparison.

Our findings pertain to three key aspects of financial inclusion: gender, income and employment status. First, there is little evidence of a gender gap in financial inclusion at the micro-level in low- and middle-income countries (LMICs) in general. In fact, women display higher levels of FI than men, as we have shown in Figures 2 and 3. We present the novel finding that such a gender gap is in fact present in high-income countries (HICs), which has hitherto not been debated in the literature. The causes of these disparities are to be addressed in future research.

Second, we find that income is not a strong determinant of financial inclusion in HICs in 2011 and 2014 but has a consistently positive effect on financial inclusion in LMICs. Income is also a predictor of financial inclusion at the macro-level across countries, where country-level scores are highly positively correlated with income per capita. Income distribution, in turn, is negatively correlated with financial inclusion, as more unequal countries have lower levels of financial inclusion. However, we stress that this correlation does not imply a specific causal direction, which may just as well run from income to financial inclusion.

Third, we conjecture that income and education have different effects across country groups due to the informality rate in the labour market. At the macro-level, self-employment is strongly and negatively correlated with financial inclusion, supporting the hypothesis put forth in this article that labour market formality is a key determinant of financial inclusion. Furthermore, women in the labour market have higher financial inclusion levels than men out of the labour force. While this link is still under-researched in the financial inclusion literature, our results suggest that this relationship should be further investigated in order to establish relevant causal mechanisms.

Overall, our analysis demonstrated the usefulness of micro-level data to measure financial inclusion. Our findings suggest that income, education and employment status are more relevant for financial inclusion than gender in LMICs. This is a significant insight for policy design and implementation, as the current focus on closing the gender gap could be shifted to fostering formal employment, further education and income generation. Finally, our new micro-level measure of financial inclusion constitutes the first step towards a dynamic comparison of financial inclusion across individuals and their relation to macroeconomic phenomena, which may stimulate further research on the causes and effects of financial inclusion.

References

Adetunji, Olubanjo Michael and Olayinka David-West. 2019. 'The Relative Impact of Income and Financial Literacy on Financial Inclusion in Nigeria'. *Journal of International Development* 31(4):312–35.

Aghion, P. and P. Bolton. 1997. 'A Theory of Trickle-Down Growth and Development'. *Review of Economic Studies* 64(2):151–72.

Allen, Franklin, Asli Demirgüç-Kunt, Leora Klapper, and Maria Soledad Martinez Peria. 2016. 'The Foundations of Financial Inclusion: Understanding Ownership and Use of Formal Accounts'. *Journal of Financial Intermediation* 27:1–30.

Amidžić, Goran, Alexander Massara, and André Mialou. 2014. *Assessing Countries' Financial Inclusion Standing - A New Composite Index*. Vol. 14. 14. Washington D.C.: International Monetary Fund.

Aslan, Goksu, Corinne Deléchat, Monique Newiak, and Fan Yang. 2017. *Inequality in Financial Inclusion and Income Inequality*. Vol. 17. 17. Washington D.C.: International Monetary Fund.

Aterido, Reyes, Thorsten Beck, and Leonardo Iacovone. 2013. 'Access to Finance in Sub-Saharan Africa: Is There a Gender Gap?' *World Development* 47:102–20.

Balliester Reis, Thereza. 2020. 'Financial Inclusion, Poverty and Income Inequality in Low- and Middle-Income Countries: A Mixed-Method Investigation'. University of Leeds, Leeds.

Banerjee, Abhijit V. and Andrew F. Newman. 1993. 'Occupational Choice and the Process of Development'. *Journal of Political Economy* 101(2):274–98.

Bateman, Milford. 2012. 'How Lending to the Poor Began, Grew, and Almost Destroyed a

Generation in India'. *Development and Change* 43(6):1385–1402.

Bateman, Milford. 2014. *The Rise and Fall of Muhammad Yunus and the Microcredit Model*. 001. Halifax.

Bateman, Milford, Maren Duvendack, and Nicholas Loubere. 2019. 'Is Fin-Tech the New Panacea for Poverty Alleviation and Local Development? Contesting Suri and Jack's M-Pesa Findings Published in Science'. *Review of African Political Economy*.

Beck, Thorsten, Asli Demirgüç-Kunt, Luc Laeven, and Ross Levine. 2004. *Finance, Firm Size, and Growth*. 10983. Cambridge, MA: National Bureau of Economic Research, Inc.

Beck, Thorsten, Asli Demirgüç-Kunt, and Ross Levine. 2007. 'Finance, Inequality and the Poor'. *Journal of Economic Growth* 12(1):27–49.

Bhatia, Shivangi and Seema Singh. 2019. 'Empowering Women Through Financial Inclusion: A Study of Urban Slum'. *VIKALPA* 44(4):182–97.

Blasius, Jörg and Michael J. Greenacre. 2014. *Visualization and Verbalization of Data*. 1st ed. Abingdon: Chapman & Hall/CRC.

Booysen, Frikkie, Servaas van der Berg, Ronelle Burger, Michael von Maltitz, and Gideon du Rand. 2008. 'Using an Asset Index to Assess Trends in Poverty in Seven Sub-Saharan African Countries'. *World Development* 36(6):1113–30.

Bouquet, Emmanuelle, Solène Morvant-Roux, and Gerardo Rodriguez-Solis. 2015. 'Agricultural Workers, Credit Rationing and Family Networks in Rural Mexico'. *Journal of Development Studies* 51(5):523–37.

Bozkurt, Ibrahim, Rıfat Karakuş, and Melek Yildiz. 2018. 'Spatial Determinants of Financial Inclusion over Time'. *Journal of International Development* 30(8):1474–1504.

Camara, Noelia and David Tuesta. 2014. *Measuring Financial Inclusion: A Multidimensional Index*. 26. Madrid: BBVA Bank, Economic Research Department.

Chakravarty, Satya R. and Rupayan Pal. 2013. 'Financial Inclusion in India: An Axiomatic Approach'. *Journal of Policy Modeling* 35(5):813–37.

Chandrasekhar, C. P. and Jayati Ghosh. 2018. 'The Financialization of Finance? Demonetization and the Dubious Push to Cashlessness in India'. *Development and Change* 49(2):420–36.

Claessens, Stijn and Luc Laeven. 2003. 'Financial Development, Property Rights, and Growth'. *The Journal of Finance* 58(6):2401–36.

Dafe, Florence. 2020. 'Ambiguity in International Finance and the Spread of Financial Norms: The Localization of Financial Inclusion in Kenya and Nigeria'. *Review of International Political Economy* 27(3):500–524.

Decancq, Koen and María Ana Lugo. 2013. 'Weights in Multidimensional Indices of Wellbeing: An Overview'. *Econometric Reviews* 32(1):7–34.

Demirgüç-Kunt, Asli, T. H. L. Beck, and P. Honohan. 2008. *Finance for All? : Policies and Pitfalls in Expanding Access*. Washington D.C.: The World Bank.

Demirgüç-Kunt, Asli and Leora Klapper. 2012a. *Financial Inclusion in Africa: An Overview*. 6088. Washington D.C.

Demirgüç-Kunt, Asli and Leora Klapper. 2012b. *Measuring Financial Inclusion: The Global Findex Database*. 6025. Washington D.C.

Demirgüç-Kunt, Asli and Leora Klapper. 2013. 'Measuring Financial Inclusion: Explaining Variation in Use of Financial Services across and within Countries'. *Brookings Papers on Economic Activity* 2013(1):279–340.

Demirgüç-Kunt, Asli, Leora F. Klapper, and Dorothe Singer. 2013. *Financial Inclusion and Legal Discrimination Against Women: Evidence from Developing Countries*. 6416. Washington D.C.

Demirgüç-Kunt, Asli, Leora Klapper, and Dorothe Singer. 2017. *Financial Inclusion and Inclusive Growth : A Review of Recent Empirical Evidence*. 8040. Washington D.C.

Demirgüç-Kunt, Asli, Leora Klapper, Dorothe Singer, Saniya Ansar, and Jake Hess. 2018. *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution*. Washington D.C.: The World Bank.

Duflo, Esther, Abhijit Banerjee, Rachel Glennerster, and Cynthia Kinnan. 2013. *The Miracle of Microfinance? Evidence from a Randomized Evaluation*. Cambridge, MA.

Dungey, Mardi, Firmin Doko Tchatoka, and María B. Yanotti. 2018. 'Using Multiple Correspondence Analysis for Finance: A Tool for Assessing Financial Inclusion'. *International Review of Financial Analysis* 59:212–22.

Duvendack, Maren and Philip Mader. 2019. *Impact of Financial Inclusion in Low- and Middle-Income Countries: A Systematic Review of Reviews*. Oslo.

Dymski, Gary A. 1995. 'The Theory of Bank Redlining and Discrimination: An Exploration'. *The Review of Black Political Economy* 23(3):37–74.

Fungáčová, Zuzana and Laurent Weill. 2015. 'Understanding Financial Inclusion in China'. *China Economic Review* 34:196–206.

Galor, Oded and Joseph Zeira. 1993. 'Income Distribution and Macroeconomics'. *The Review of Economic Studies* 60(1):35.

Ghosh, Saibal and D. Vinod. 2017. 'What Constrains Financial Inclusion for Women? Evidence from Indian Micro Data'. *World Development* 92:60–81.

Greenacre, Michael and Jorg Blasius. 2006. *Multiple Correspondence Analysis and Related Methods*. Vol. 1. 1st ed. edited by M. Greenacre and J√∂rg Blasius. Boca Raton: Chapman and Hall/CRC.

Guérin, Isabelle. 2014. ‘Juggling with Debt, Social Ties, and Values’. *Current Anthropology* 55(S9):S40–50.

Guérin, Isabelle, Bert D’Espallier, and Govindan Venkatasubramanian. 2013. ‘Debt in Rural South India: Fragmentation, Social Regulation and Discrimination’. *Journal of Development Studies* 49(9):1155–71.

Honohan, Patrick. 2004. *Financial Development, Growth and Poverty: How Close Are the Links?* 3202. Washington D.C.: Palgrave Macmillan UK.

Honohan, Patrick. 2008. ‘Cross-Country Variation in Household Access to Financial Services’. *Journal of Banking & Finance* 32(11):2493–2500.

Husson, Francois and Julie Josse. 2014. ‘Multiple Correspondence Analysis’. Pp. 165–82 in *Visualization and verbalization of data,* edited by J. Blasius and M. J. Greenacre. Boca Raton: CRC Press.

ILO. 2016. *Minimum Wage Policy Guide*. Geneva.

ILO. 2017. *World Social Protection Report 2017-19: Universal Social Protection to Achieve the Sustainable Development Goals*. Geneva.

ILO. 2018. *Women and Men in the Informal Economy: A Statistical Picture*. 3rd ed. Geneva: ILO.

Johnson, Susan and Max Nino-Zarazua. 2011. ‘Financial Access and Exclusion in Kenya and Uganda’. *Journal of Development Studies* 47(3):475–96.

Kaffenberger, Michelle and Edoardo Totolo. 2018. *A Digital Credit Revolution - Insights from Borrowers in Kenya and Tanzania*. Nairobi.

Karim, Lamia. 2011. *Microfinance and Its Discontents: Women in Debt in Bangladesh*. Baltimore: University of Minnesota Press.

Karpowicz, Izabela. 2016. 'Financial Inclusion, Growth and Inequality: A Model Application to Colombia'. *Journal of Banking and Financial Economics* 2016(2):68–89.

Khan, Mohsin S. and Abdelhak Senhadji. 2000. *Financial Development and Economic Growth: An Overview*. 00/209. Washington, DC: IMF.

Klapper, Leora and Dorothe Singer. 2017. 'The Role of Demand-Side Data – Measuring Financial Inclusion from the Perspective of Users of Financial Services'. Pp. 1–15 in. Marrekech: Bank for International Settlements.

Levine, Ross. 1997. 'Financial Development and Economic Growth: Views and Agenda'. *Journal of Economic Literature* 35(2):688–726.

Leyshon, Andrew and Nigel Thrift. 1995. 'Geographies of Financial Exclusion: Financial Abandonment in Britain and the United States'. *Transactions of the Institute of British Geographers* 20(3):312.

Li, Linyang. 2018. 'Financial Inclusion and Poverty: The Role of Relative Income'. *China Economic Review* 52:165–91.

Lindsjö, Karin. 2018. 'The Financial Burden of a Fee Free Primary Education on Rural Livelihoods–a Case Study from Rural Iringa Region, Tanzania'. *Development Studies Research* 5(1):26–36.

Lotto, Josephat. 2018. 'Examination of the Status of Financial Inclusion and Its Determinants in Tanzania'. *Sustainability* 10(2873):1–15.

Lusardi, Annamaria and Peter Tufano. 2015. ‘Debt Literacy, Financial Experiences, and Overindebtedness’. *Journal of Pension Economics and Finance* 14(4):332–68.

Mader, Philip. 2018. ‘Contesting Financial Inclusion’. *Development and Change* 49(2):461–83.

Mader, Philip and Sophia Sabrow. 2015. ‘All Myth and Ceremony? Examining the Causes and Logic of the Mission Shift in Microfinance from Microenterprise Credit to Financial Inclusion’. *Forum for Social Economics* 1–27.

Murendo, Conrad, Gamuchirai Murenje, Pepukai Prince Chivenge, and Rumbidzai Mtetwa. 2021. ‘Financial Inclusion, Nutrition and Socio-Economic Status Among Rural Households in Guruve and Mount Darwin Districts, Zimbabwe’. *Journal of International Development* 33(2):86–108.

National Financial Inclusion Council. 2017. *National Financial Inclusion Framework 2018-2022: A Public-Private Stakeholder Initiative*. Dar es Salaam.

Park, Cyn-Young and Rogelio Mercado. 2018. ‘Financial Inclusion, Poverty, and Income Inequality’. *The Singapore Economic Review* 63(01):185–206.

Pasha, Atika. 2017. ‘Regional Perspectives on the Multidimensional Poverty Index’. *World Development* 94:268–85.

Pesqué-Cela, Vanesa, Lihui Tian, Deming Luo, Damian Tobin, and Gerhard Kling. 2021. ‘Defining and Measuring Financial Inclusion: A Systematic Review and Confirmatory Factor Analysis’. *Journal of International Development* 33(2):316–41.

Piñeyro, César Manuel Zulaica. 2013. ‘Financial Inclusion Index: Proposal Of A Multidimensional Measure For Mexico’. *Mexican Journal of Economics and Finance* 8(2):157–80.

Pollard, J. S. 1996. ‘Banking at the Margins: A Geography of Financial Exclusion in Los Angeles’. *Environment and Planning A* 28(7):1209–32.

Rewilak, Johan. 2017. ‘The Role of Financial Development in Poverty Reduction’. *Review of Development Finance* 7(2):169–76.

Reymão, Ana Elizabeth Neirão and Felipe Guimarães de Oliveira. 2017. ‘Inclusão Financeira e Vulnerabilidade Do Consumidor de Crédito Habitacional: Uma Análise Jurídico-Econômica Do Mercado Brasileiro’. *Revista de Direito, Globalização e Responsabilidade Nas Relações de Consumo* 3(2):1–21.

Sarma, Mandira. 2016. ‘Measuring Financial Inclusion Using Multidimensional Data’. *World Economics* 17(1):15–40.

Sarma, Mandira and Jesim Pais. 2011. ‘Financial Inclusion and Development’. *Journal of International Development* 23(5):613–28.

Sethi, Dinabandhu and Debashis Acharya. 2018. ‘Financial Inclusion and Economic Growth Linkage: Some Cross Country Evidence’. *Journal of Financial Economic Policy* 10(3):369–85.

Shafiq, M. Najeeb. 2009. ‘A Reversal of Educational Fortune? Educational Gender Gaps in Bangladesh’. *Journal of International Development* 21(1):137–55.

Shimeles, Abebe and Mthuli Ncube. 2015. ‘The Making of the Middle-Class in Africa: Evidence from DHS Data’. *Journal of Development Studies* 51(2):178–93.

Suri, Tavneet and William Jack. 2016. ‘The Long-Run Poverty and Gender Impacts of Mobile Money.’ *Science (New York, N.Y.)* 354(6317):1288–92.

Swamy, Vighneswara. 2014. ‘Financial Inclusion, Gender Dimension, and Economic Impact on Poor Households’. *World Development* 56:1–15.

Tran, Tam Ngo Minh and Laure Pasquier-Doumer. 2019. ‘Full-Day Schooling and Educational Inequality in Vietnam’. *Journal of Development Studies* 55(5):786–804.

Ulwodi, Dunstone W. and Peter W. Muriu. 2017. ‘Barriers of Financial Inclusion in Sub-Saharan Africa’. *Journal of Economics and Sustainable Development* 8(14):66–81.

United Nations Children’s Fund, UN Women, and Plan International. 2020. *New Era for Girls: Taking Stock of 25 Years of Progress*. New York.

Velasco, Carmen and Reynaldo Marconi. 2004. ‘Group Dynamics, Gender and Microfinance in Bolivia’. *Journal of International Development* 16(3):519–28.

Wang, Xiuhua and Jian Guan. 2017. ‘Financial Inclusion: Measurement, Spatial Effects and Influencing Factors’. *Applied Economics* 49(18):1751–62.

Williams, Timothy P., Pamela Abbott, and Alfred Mupenzi. 2015. ‘“Education at Our School Is Not Free”: The Hidden Costs of Fee-Free Schooling in Rwanda’. *Compare* 45(6):931–52.

World Bank. 2014. *Global Financial Development Report 2014: Financial Inclusion*. Washington D.C.: The World Bank.

World Economic Forum. 2021. *Global Gender Gap Report 2021*. Geneva.

Zhang, Quanda and Alberto Posso. 2019. ‘Thinking Inside the Box: A Closer Look at Financial Inclusion and Household Income’. *Journal of Development Studies* 55(7):1616–31.

Zins, Alexandra and Laurent Weill. 2016. ‘The Determinants of Financial Inclusion in Africa’. *Review of Development Finance* 6(1):46–57.

Online Appendix

A.1 Existing cross-country indexes of financial inclusion

Table A.1: *Summary 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)[33]	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

[33] The study does not define the dimensions, so I allocate them on my own discretion to make it comparable across studies.

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[34] 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)
				Usage	Total volume of credit/ deposit/ mobile money transactions as % of GDP

[34] Lakh is a unit in the Indian numbering system equal to one hundred thousand

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

A.2 Variables description and creation

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	[Variable created by author, more information below]	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.	N/A

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.	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.	N/A
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.

Mobile Money Account

A measurement issue that has risen while analysing the data is that in 2011, there are three variables to measure Mobile Money (Mobile phone to pay bills, Mobile phone to send money, Mobile phone to receive money). To address this issue and ensure comparability with 2014 and 2017, we create a new variable 'Mobile Account', in which if any of the three Mobile Money variables were positive, the new variable would also be positive.

A.3 Robustness checks

Table A.3. *Results without the quadratic term for age*

	(1) 2011	(2) 2014	(3) 2017	(4) 2011	(5) 2014	(6) 2017
female	-0.13	-0.02	1.28***	-2.82***	-0.81**	-0.25
	(0.13)	(0.19)	(0.31)	(0.56)	(0.38)	(0.41)
1.educ	.	.	.	.	.	.
2.educ	1.22***	2.38***	2.99***	1.09*	2.06***	0.84
	(0.12)	(0.21)	(0.24)	(0.58)	(0.55)	(0.65)
3.educ	2.49***	4.55***	5.32***	-0.16	2.12***	0.40
	(0.19)	(0.26)	(0.27)	(0.89)	(0.77)	(0.83)
1.inc	.	.	.	.	.	.
2.inc	0.44***	0.82***	0.72***	0.91***	0.71***	0.96***
	(0.08)	(0.13)	(0.14)	(0.23)	(0.23)	(0.23)
3.inc	0.77***	1.49***	1.79***	0.94***	1.10***	1.52***
	(0.08)	(0.13)	(0.16)	(0.33)	(0.24)	(0.26)
4.inc	1.25***	2.33***	2.57***	1.01**	1.59***	1.54***
	(0.10)	(0.16)	(0.17)	(0.42)	(0.25)	(0.27)
5.inc	1.84***	3.21***	3.49***	-0.20	1.25***	1.71***
	(0.11)	(0.18)	(0.22)	(0.41)	(0.27)	(0.32)
work	.	.	2.50***	.	.	4.05***
			(0.17)			(0.29)
fem*educ1	.	.	.	.	.	.
fem*educ2	0.02	-0.08	-0.60***	0.79*	0.54	0.59
	(0.08)	(0.14)	(0.19)	(0.43)	(0.35)	(0.39)
fem*educ3	-0.12	-0.31	-1.08***	0.99*	0.60	1.05**
	(0.14)	(0.21)	(0.26)	(0.50)	(0.38)	(0.46)
fem*inc1	.	.	.	.	.	.
fem*inc2	-0.12	-0.24*	-0.28**	-0.36	-0.11	-0.39*
	(0.10)	(0.14)	(0.13)	(0.29)	(0.31)	(0.22)
fem*inc3	-0.20**	-0.22	-0.81***	-0.64*	-0.31	-0.27
	(0.09)	(0.14)	(0.17)	(0.32)	(0.29)	(0.26)
fem*inc4	-0.33***	-0.50***	-0.89***	-0.77*	-0.52*	-0.32
	(0.10)	(0.13)	(0.18)	(0.38)	(0.28)	(0.23)
fem*inc5	-0.47***	-0.62***	-0.96***	-0.14	-0.46*	-0.41
	(0.10)	(0.14)	(0.23)	(0.42)	(0.27)	(0.27)
fem*work	.	.	-0.36**	.	.	-0.82***
			(0.15)			(0.27)
age	0.01***	0.04***	0.05***	-0.07***	-0.04***	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
lgdppcavg	0.64***	1.06***	0.82**	0.17	1.38**	1.48**
	(0.17)	(0.33)	(0.40)	(0.74)	(0.58)	(0.64)
lpopavg	-0.02	0.22**	0.29**	-0.33**	0.01	0.15
	(0.05)	(0.11)	(0.13)	(0.14)	(0.13)	(0.14)
ruleavg	0.40**	0.81***	0.97***	4.33***	1.87***	2.79***
	(0.16)	(0.23)	(0.32)	(0.72)	(0.35)	(0.51)
ATMs	0.01	0.02***	0.02***	0.01***	0.01**	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
branch	0.01	0.01	0.01	-0.00	-0.00	0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
rural	0.02***	0.03**	0.03**	0.01	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
unemp	-0.02	-0.04	0.01	0.02	0.04	0.02
	(0.02)	(0.03)	(0.03)	(0.05)	(0.05)	(0.03)

Constant	9.55***	16.19***	10.79**	24.94***	22.09***	13.46*
	(1.53)	(3.58)	(4.58)	(5.73)	(6.03)	(7.06)
Observations	96,727	89,704	85,557	37,041	40,650	39,149
R-squared	0.14	0.19	0.21	0.13	0.13	0.17

***statistically significant at the 1% level; ** at the 5% level; * at the 10% level using the t-test

Note: Clustered standard errors in parentheses. The financial inclusion variable ranges from 0 to 100.

Table A.4. *Results for the full sample (both low- and middle-income countries and high-income countries)*

	(1) 2011	(2) 2014	(3) 2017
female	-0.61***	-0.24	0.63**
	(0.16)	(0.17)	(0.25)
1.educ	.	.	.
2.educ	1.49***	2.30***	2.76***
	(0.15)	(0.18)	(0.24)
3.educ	1.69***	3.12***	3.54***
	(0.31)	(0.31)	(0.40)
1.inc	.	.	.
2.inc	0.44***	0.67***	0.73***
	(0.10)	(0.11)	(0.12)
3.inc	0.61***	1.23***	1.60***
	(0.13)	(0.11)	(0.14)
4.inc	0.97***	1.94***	2.12***
	(0.16)	(0.13)	(0.15)
5.inc	1.02***	2.46***	2.84***
	(0.18)	(0.17)	(0.19)
work	.	.	2.17***
			(0.14)
fem*educ1	.	.	.
fem*educ2	-0.35**	-0.11	-0.50***
	(0.13)	(0.14)	(0.19)
fem*educ3	-0.64***	-0.17	-0.40
	(0.20)	(0.19)	(0.26)
fem*inc1	.	.	.
fem*inc2	-0.06	-0.09	-0.25**
	(0.12)	(0.13)	(0.12)
fem*inc3	-0.10	-0.12	-0.54***
	(0.13)	(0.12)	(0.14)
fem*inc4	-0.22	-0.37***	-0.56***
	(0.14)	(0.12)	(0.14)
fem*inc5	-0.11	-0.39***	-0.66***
	(0.16)	(0.13)	(0.18)
fem*work	.	.	-0.21
			(0.16)
age	0.24***	0.32***	0.30***
	(0.02)	(0.01)	(0.02)
age2	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)
lgdppcavg	1.09***	1.28***	1.26***
	(0.24)	(0.27)	(0.34)
lpopavg	-0.17**	0.15	0.17
	(0.07)	(0.10)	(0.11)
ruleavg	1.87***	1.44***	1.86***
	(0.28)	(0.21)	(0.28)
ATMs	0.01***	0.00	0.01***
	(0.00)	(0.00)	(0.00)
branch	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)
rural	0.03***	0.02*	0.02

	(0.01)	(0.01)	(0.01)
unemp	-0.07***	-0.04	-0.03
	(0.02)	(0.02)	(0.02)
Constant	6.31**	12.45***	7.61*
	(2.64)	(3.48)	(4.00)
Observations	133,768	130,354	124,706
R-squared	0.32	0.32	0.34

***statistically significant at the 1% level; ** at the 5% level; * at the 10% level using the t-test

Note: Clustered standard errors in parentheses. The financial inclusion dependent variable ranges from 0 to 100.

Table A.5. *Results without control variables*

	(1) 2011	(2) 2014	(3) 2017	(4) 2011	(5) 2014	(6) 2017
female	-0.19	0.00	0.94***	-3.13***	-0.76*	-0.65*
	(0.12)	(0.17)	(0.26)	(0.61)	(0.39)	(0.39)
1.educ	.	.	.	.	.	.
2.educ	1.07***	2.31***	3.14***	0.37	1.54***	0.50
	(0.13)	(0.19)	(0.21)	(0.56)	(0.49)	(0.64)
3.educ	2.15***	4.28***	5.36***	-1.16	1.27*	-0.18
	(0.21)	(0.23)	(0.23)	(0.83)	(0.70)	(0.82)
1.inc	.	.	.	.	.	.
2.inc	0.49***	0.79***	0.76***	0.74***	0.63**	0.96***
	(0.08)	(0.11)	(0.13)	(0.23)	(0.24)	(0.21)
3.inc	0.82***	1.41***	1.71***	0.91**	1.14***	1.42***
	(0.10)	(0.12)	(0.14)	(0.34)	(0.23)	(0.24)
4.inc	1.31***	2.26***	2.55***	0.90**	1.52***	1.52***
	(0.11)	(0.15)	(0.15)	(0.41)	(0.24)	(0.26)
5.inc	1.83***	3.14***	3.46***	-0.35	1.22***	1.72***
	(0.11)	(0.16)	(0.19)	(0.41)	(0.26)	(0.31)
Work	.	.	1.80***	.	.	2.66***
			(0.14)			(0.23)
fem*educ1	.	.	.	.	.	.
fem*educ2	0.06	-0.05	-0.56***	0.81*	0.26	0.44
	(0.08)	(0.14)	(0.17)	(0.44)	(0.33)	(0.36)
fem*educ3	0.02	-0.18	-0.78***	1.01*	0.31	0.81*
	(0.14)	(0.21)	(0.24)	(0.51)	(0.35)	(0.44)
fem*inc1						
fem*inc2	-0.13	-0.23*	-0.26**	-0.15	0.04	-0.23
	(0.09)	(0.12)	(0.12)	(0.32)	(0.30)	(0.22)
fem*inc3	-0.17**	-0.19	-0.72***	-0.42	-0.17	0.13
	(0.09)	(0.13)	(0.15)	(0.32)	(0.25)	(0.27)
fem*inc4	-0.30***	-0.49***	-0.80***	-0.52	-0.37	-0.02
	(0.09)	(0.13)	(0.16)	(0.38)	(0.26)	(0.22)
fem*inc5	-0.39***	-0.63***	-0.93***	0.14	-0.23	-0.15
	(0.10)	(0.13)	(0.20)	(0.43)	(0.25)	(0.25)
fem*work	.	.	-0.03	.	.	-0.52**
			(0.16)			(0.23)
age	0.16***	0.28***	0.25***	0.36***	0.35***	0.35***
	(0.01)	(0.01)	(0.02)	(0.05)	(0.03)	(0.03)
age2	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lgdppcavg	0.44***	0.79***	0.88***	-0.15	1.34**	1.52***
	(0.09)	(0.16)	(0.19)	(0.71)	(0.55)	(0.51)
lpopavg	0.10	0.26**	0.31**	-0.07	0.14	0.17
	(0.07)	(0.12)	(0.14)	(0.11)	(0.10)	(0.10)
ruleavg	0.59***	1.15***	1.40***	4.55***	1.84***	2.80***
	(0.19)	(0.30)	(0.30)	(0.62)	(0.37)	(0.49)
Constant	7.89***	15.16***	9.07***	17.05***	14.06**	7.41
	(1.47)	(2.82)	(3.26)	(6.22)	(5.62)	(5.39)
Observations	106,422	100,667	107,448	38,998	44,091	42,195
R-squared	0.15	0.21	0.21	0.16	0.16	0.19

***statistically significant at the 1% level; ** at the 5% level; * at the 10% level using the t-test

Note: Clustered standard errors in parentheses. The financial inclusion variable ranges from 0 to 100.

A.4 The Global Ranking of Financial Inclusion

Table A.6. *The Global Ranking of Financial Inclusion (GRFI)*

Rank	**GRFI 2011**	**Score**	**GRFI 2014**	**Score**	**GRFI 2017**	**Score**
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