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Financial Inclusion, Inequality in Financial Access and Income Inequality – Evidence from European Countries

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1. Introduction

Financial non-inclusion and financial illiteracy are basically the problems of economically vulnerable population. A notable share of the population in the developing regions in Europe and also in other continents still are unbanked and the major part of them are women even in the era of highly technology driven globalised world. While in the high-income regions of Europe most adults have access to bank and other financial institutions, the less developed parts of Europe have much lower levels of banked adults. Several Reports based on Global *Findex* database reveal that lack of trust in institutions is a major issue for many people remain unbanked. Gender gap in financial inclusion is another issue particularly in countries like Turkey where just above 50 per cent of women have bank account. Financial non-inclusion is associated with non-inclusion in labour market contributing to income inequality and slow economic growth.

Access to finance is one of the important issues in the financial system. Greater access is expected to foster financial inclusion when access levels are below the threshold. Also increasing access creates financial system more competitive. If financial development is non-inclusive and financial institutions are not accessible to larger part of the economic agents (households and firms), its contributions to economic growth would be limited (Jinjarak, and Park 2015). In this study, we define financial inclusion as ability of economic agents to access financial services from formal financial institutions and financial markets[1].

If financial inclusion is treated as a choice problem, individuals will take decision whether to participate in the formal financial system by maximizing utility given their budget constraints.

[1] Formal financial institutions include banks, insurance companies, mutual funds, and pension funds. Financial markets include stock and bond markets.

From an agent's point of view, financial exclusion may be voluntary or involuntary. In some cases, individuals do not prefer formal financial services, because of cultural reasons, lack of money or ignorance about the benefits of these services. Imperfect information about the utility of financial services has an important role in explaining voluntary exclusion. But, involuntary exclusion appears primarily because of lack of access to formal financial services. Barriers in access to financial services create a limit in use of them. However, greater access does not necessarily imply greater use of financial services. As only access does not imply a usage because of income and other socio-economic factors, regulatory framework or cultural habits, we need different dimensions of financial inclusion.

Theoretical models predict that financial inclusion enhances growth and reduces income inequality in presence of financial frictions (Galor and Zeira 1993; Aghion and Bolton 1997; Galor and Moav 2004). The low-income people, particularly the poor, have very limited access to finance because of their binding constraints in information and transaction costs. Thus, the inclusion of these people in financial development will facilitate funding to them that will reduce income inequality. Some scholars like Greenwood and Jovanovic (1990) argued that the relationship between financial inclusion and inequality is inverted U shaped implying that at the early stage of financial development only the rich people can afford to financial market raising inequality, while in the later phase of financial development inclusion becomes widely distributed reducing inequality. In a theoretical model, Dabla Norris et al. (2015) has shown that although financial inclusion in the shape of increasing access of the poor reduces income inequality, inclusion in the form relaxing borrowing constraint can benefit wealthy agents disproportionately that will increase inequality. Thus, the theory is inconclusive on the direction of causality between financial development and income inequality.

Against this backdrop, this study contributes to the literature by providing an objective measure of financial inclusion, inequality in access to finance and examining the variation in financial inclusion among top 15 poorest countries in Europe using microdata from the *Global Findex*. In this study, we construct scores of two dimensions of financial inclusion: access to finance, and usage of financial services. A composite index is constructed by taking these three dimensions together at micro level by applying correspondence analysis with Findex survey data. The study also investigates the role of inequality in financial inclusion in explaining income inequality based on a composite financial inclusion index constructed by using correspondence analysis in low income European countries during 2011-2021.

2. Methodology

We have considered two dimensions of financial inclusion: access to finance, and usage of financial services. Access to finance like expansion of bank branches particularly in rural areas indicates depth of financial services, usage like number of transactions per bank account provides the incidence of use of financial services, quality describes how financial services fulfill individuals' needs. In calculating financial inclusion index, Sarma (2012) computed the sub-index of different dimensions and aggregated each index as the normalized inverse of the Euclidean distance, where the distance is calculated from a reference point and normalized by the number of dimensions included in the composite index. However, in this study, the weights assigned for each dimension are subjectively chosen based on the author's intuition. Amidžić et al. (2014) constructed a financial inclusion index using factor analysis (FA) to determine dimensions and weights. Cámara &Tuesta (2014), applied two-stage principal component analysis (PCA) for the construction of a multidimensional financial inclusion index. In the first stage, PCA is used to estimate the weights of three sub-indices or dimensions of financial inclusion. In the second stage, again PCA is applied to estimate the overall financial inclusion index by using the previous sub-indices as causal variables.

As most of the information on financial inclusion are categorical, the use of PCA may not be appropriate to construct the composite index. Categorical variables often do not have comparable scale and distance properties, and these variables cannot be analysed with simple frequencies. Correspondence analysis (CA) resolves the problem by providing nominal measure for each categorical variable in terms of the notion of distance. In this study, CA is used to calculate scores of financial inclusion. The CA is helpful in understanding the similarities between the categories of variables and the association between the variables. In some sense, CA is similar to principal components for nominal variables. In CA, the aim is to maximize the correlation between the scored row and column of a contingency table. The optimal scores are the coordinates on the first dimension. The coordinates on the second and subsequent dimensions maximize the correlation between row and column scores subject to orthogonality constraints. By using singular value decomposition all categorical variables can be treated simultaneously in the form of a point cloud.

Suppose that the multidimensional data set is given in the form of a numerical matrix Z(*n*, *m*), where *n* is the number of observation units, and *m* is the number of variables measured on each observation unit. Each unit in the sample space is represented by a vector of order *m*. In CA, the dissimilarities between sample units is measured by a metric, called distance, on the population space. The distance between units in the sample space is measured by inertia, a measure of the information contained in the data set. The concept of inertia is derived from static mechanics and is geometric in nature. Inertia is Pearson's χ^2 statistic divided by sample size.

The inertia approach of CA relies on within-distribution distances in the sample space. In this approach, the sample space of *n* units is looked at as a cloud of points in the *m* dimensional space, with a mass, called weight, associated to each point. The cloud has a centroid measuring weighted mean. The weighted sum of distances to the centroid gives the total inertia of the cloud of observation-points.

The CA provides an optimal space of low dimension p ($p<m$), where the projected cloud of sample units keeps as much as possible of the inertia of the source cloud or by minimising the inertia loss. Similar to PCA, it is a data reduction technique that minimizes the unavoidable information-loss generated by representing the observation units in a lower dimension space. In this method, each sample unit is represented by a set of coordinates in the optimal *p*-dimension space called its scores which is a linear combination of the original *m* observed variables.

In measuring financial inclusion the multiple correspondence analysis (MCA), an extension of CA for more variables, may be the appropriate one. The MCA is a special case of generalized canonical analysis, and is applied to categorical data. Let $x_1, x_2, x_3, \ldots\ldots, x_m$ be *m* categorical variables on *n* observations in a sample. Each variable x_j is assumed to have k_j distinct categories and is looked at as an $n \times k_j$ orthogonal binary matrix $Z^{(j)}$, called the indicator matrix which is generated from the categorical indicators. As the columns of $Z^{(j)}$sum to 1, the Mahalanobis metric in canonical analysis is equivalent to the χ^2 metric in the case of MCA.

In MCA, the weight of a categorical variable is obtained by quantifying each primary qualitative indicator in a non-linear way without imposing any constraint on a functional form. Thus, MCA is a CA based on the Burt matrix of all the 2-way contingency tables generated from k_j primary indicators.

We define $Z = (Z^{(1)} \quad \dots \quad Z^{(m)})$ as the $n \times k$ indicator matrix of the set of *x* variables,

where $k = k_1 + k_2 + \cdots + k_m$

An observation unit with k indicators is a line-vector of numbers 1 to k, and the value of the composite indicator is simply the average of category-weights.

Let the h_{th} category of j_{th} variable for i_{th} observation be denoted as

$$Z_{ih}^{(j)} = 1 \; if \; x_{ij} = h$$

Here, i=1, 2, …n denotes observation; j= 1,2,…k denotes variable; and h = 1, 2,…. n_j denotes category.

With *n* observation units, the profile of category *h* of variable *j* is a column-vector of numbers 1 to $Z_h^{(j)}$, $Z_h^{(j)} = \sum_{i=1}^{n} Z_{ih}^{(j)}$.

A category weight is the average of the normalized scores of the population units belonging to this category.

On the basis of the indicator matrix Z we can define the Burt matrix as

$$B = Z'Z = Z'D(w)Z$$

Where $D(w)$ is $q \times q$ square matrix with weights on the diagonal and 0 off diagonal.
The diagonal block of B associated with variable x_j is a diagonal matrix with the frequencies of x_j on the diagonal. The off-diagonal block of B associated with variables x_j and x_l is the two-way cross-tabulation of x_j and x_l.

We define another Burt matrix by taking cross tabulation of supplementary variables with more rows:

$$B^* = Z^{*\prime}Z$$

where Z^* is the indicator matrix with more columns for the supplementary variables.

Define $B_{++} = \sum_{l=1}^{k} \sum_{m=1}^{k} B_{lm}$

$P = \frac{B}{B_{++}}$

$c = \sum_{l=1}^{k} P_{l*} = P_{+*} = P'I$

$S = D(c)^{-1/2}(P - cc')D(c)^{-1/2}$

Here, c is the column mass, $D(c)^{-1/2}$ is the diagonal matrix with elements $\frac{1}{c_t}$, c_t is an element of c

The spectral or eigen decomposition of the square symmetric matrix S is

$$S = V\Phi V'$$

This is the singular value decomposition in correspondence analysis. The standard column coordinates A is

$$A = D(c)^{-1/2}V$$

In the indicator approach to MCA, the inertia of column j is

$$In_h^{(j)} = \sum_{i=1}^{n} w_i \frac{\left(Z_{ih}^{(j)} - mc_h^{(j)}\right)^2}{m^2 c_h^{(j)} w_+}$$

where $Z_{ih}^{(j)}$ is the (i,h) th element of the indicator matrix for variable j, w_i is the weight for observation *i*, *m* is the number of active variables, $c_h^{(j)}$ is the column mass of variable *j* for category *h*, and w+ is the sum of the weights over the observations.

If t_{th} principal inertia is λ_t, the t_{th} diagonal element of Φ, the total inertia will be $\sum_t \lambda_t$

In the Burt approach to MCA, the unadjusted principal inertia is λ_t^2, and the total unadjusted inertia is $\sum_t \lambda_t^2$

The adjusted principal inertia,

$\lambda_t^{adj} = \left(\frac{m}{m-1}\right)^2 \left(\lambda_t^2 - \frac{1}{m}\right)^2$ provided $m\lambda_t > 1$

Total inertia = $\left(\frac{m}{m-1}\right) \sum_t \lambda_t^2 - \frac{q-m}{m^2}$

The standard coordinates are independent of the principal inertia; with or without adjustment, these are defined as before

$$A = D(c)^{-1/2}V$$

The principal coordinates F are defined as

$$F = AD\Lambda^{\frac{1}{2}}$$

where Λ is a vector of adjusted or unadjusted principal inertias and $D\Lambda^{\frac{1}{2}}$ is the diagonal matrix with elements $\lambda_t^{1/2}$ on the diagonals.

The coordinates of supplementary variables are computed as weighted averages of the column coordinates by using the CA transition formula. As outlined by Greenacre (2006), standard coordinates may be used for averaging, with the profiles of the indicator representation of supplementary columns as weights. Supplementary principal column coordinates are computed as weighted averages of the standard active column coordinates, and then supplementary standard coordinates are computed by division by the principal inertias.

The first step of this method is to construct a contingency table to find out the association between qualitative responses. Correspondence analysis utilizes the association between rows and columns. The weighted χ^2 distances between two individual columns can be found by applying the following formula:

$$D_{\chi^2}(C, C') = \sqrt{\sum_{r=1}^{R} \frac{N_{++}}{N_{r+}} \left(\frac{N_{rc}}{N_{+c}} - \frac{N_{rc'}}{N_{+c'}} \right)^2}$$

	Q21	Q22	Q23	Row total
Q11	N11	N12	N13	N1+
Q12	N21	N22	N23	N2+
Q13	N31	N32	N33	N3+
Q14	N41	N42	N43	N4+
Column total	N+1	N+2	N+3	N++

CA analyses a two-way contingency table.

3. Data

This study uses different financial indicators provided in the Global Findex micro level data. It provides information on financial services and the intensity of their use based on a worldwide survey of representative samples of around 1000 individuals from each country focusing on demand side of financial services. The information are available on account ownership, payments, saving, credit, and financial resilience by country, region, and income group for 2011, 2014, 2017 and 2021. This dataset is used for demand side analysis of access to finance for individuals with age 15 and above. Global Findex 2021 survey data covers 127,854 adults in more than 120 economies during the COVID-19 pandemic. In 2011 and 2014, this survey covered information about 150,000 randomly selected adults from 140 and 137 countries around the world. The survey has been conducted by following multi stage stratified random sampling. Primary sampling units are stratified by population size and geographical locations or both, and selection is based on probabilities proportional to population size, or by using simple random sampling. Appropriate weighting is used to ensure a nationally representative sample for each economy.

This study concentrates on financial inclusion in 15 poorest countries of Europe in terms of GDP per capita. Access to finance and use of financial services are the major dimensions of financial inclusion. Ownership of bank account, debit card, credit card, and access to internet for financial transaction are taken as indicators of access to finance. Use of bank account, debit card, credit card, and other online transactions are considered as use indicators. This study uses the Global Findex micro level data for 2011 and 2021. The number of sample adults for 2021 is 12893 after deleting no response and refuse to response units for 15 poorest sample countries of Europe, while the effective sample size for 2011is 15650.

4. Observed facts

Access to bank, measured by the proportion of bank account ownership[2], is the fundamental measure of financial inclusion, particularly in the developing world. The Report based on Global Findex 2021 survey data highlights that the share of adults with bank account increased globally from 51 percent in 2011 to 76 per cent in 2021. The gender gap in account holding declined from 9 per cent to 6 per cent in developing economies during this period. In developing economies around 18 per cent of adults used bank transfer for paying utility bill in 2021, and one third among them used such type of transfer first time after the onset of the COVID-19 pandemic. Despite the increase in bank account for all adults, women, and those outside the workforce are lagging behind the men who are in workforce and earn higher

[2] The Global Findex 2021 defines account ownership of an individual or jointly owned account at a regulated financial institutions like bank, credit union, microfinance institution, post office, or mobile money service provider.

income. In 2021, 74 percent of men but only 68 percent of women in developing economies had an account.

Expansion of account ownership in formal financial institutions is not sufficient for financial inclusion. Another dimension of financial inclusion is the increase in use of accounts for digital transaction, saving, borrowing and other financial services. The Global Findex 2021 survey highlighted that 84 percent of account owners in the globe used their accounts for digital payment at least once, the respective proportions in high income countries and developing countries were 98 per cent and 80 per cent. The increase in account ownership can enhance financial empowerment of individuals, particularly among women. It is observed that the women enjoy greater control over their income which increases household bargaining power for them because of the use of bank account in salary payment (Field et al. 2021).

Table 1 shows the percentage share of adult people in 15 top rich countries and 15 top poorest countries in Europe in 2011 and 2021. A sharp contrast is observed between the rich and poor countries in Europe in intensity in financial services. The intensity of access to financial services in terms of percentage share of adults was nearly half or less than half in the poorer part of Europe as compared to the richer part in 2011. Although the situation improved over the 10 year period, the people living in the less developed part are still lagging behind those in the developed part in inclusiveness of financial services. Thus appropriate policies, and incentives are needed to increase the use of accounts for payments, savings, and credit.

Table 1 Percentage of European people in financial services

	2011		2021	
	Rich countries	Poor countries	Rich countries	Poor countries
Access indicators				
Ownership of account at a financial institution	94	52	99	79
Ownership of debit card	77	39	92	60
Ownership of credit card	48	16	55	28
Use indicators				
Use electronic payment	69	21	75	56
Use account at a financial institution for saving	79	43	61	18

Borrow from a financial institution	16	10	16	15
Use Debit Card			93	76
Use Credit Card			82	78
Quality indicators				
Made any deposit into the account			89	82
Withdrew from the account			91	84
Made bill payments online using the Internet			65	40
Bought something online using the Internet			67	37

Source: Author's calculation with Global Findex micro level data

5. Empirical findings

5.1 Determination of financial inclusion index

Adults with age 15 and above from 15 poorest European countries for 2011 and 2021 are the sample units of this study. As the access and use indicators are categorical variables, we have converted all indicators in binary form with 1 for having access and 0 for not having access. The financial inclusion index is calculated by using the following 2 step method. Access to finance and use of finance are considered as two major dimensions of financial inclusion. In step 1, access index scores and use index scores are calculated by using MCA. Ownership of account at any financial institution, ownership of debit card and ownership of credit card are used to calculate the composite scores for access indicators. Use of bank account for savings and borrowings, use of debit and credit cards for financial transactions are the components of the composite index scores of use indicators. Weights of different components are expected to be different and are estimated by applying MCA. Since countries could be different in access to and use of financial services, we have calculated these index scores separately for each country. In step 2, financial inclusion index is calculated by taking access index scores and use index scores as two major dimensions of it. Weights of these two dimensions are endogenously determined. As the scores are the predicted values and are quantitative in nature, PCA is used in this step to calculate financial inclusion index score. The PCA is calculated for each country in the sample separately. The first principal component capturing the maximum variance is considered for calculating the composite index. At the final stage, the composite financial index scores are grouped into 5 equal parts with values 1, 2, 3, 4, and 5. The higher the index, higher is the inclusiveness of the person.

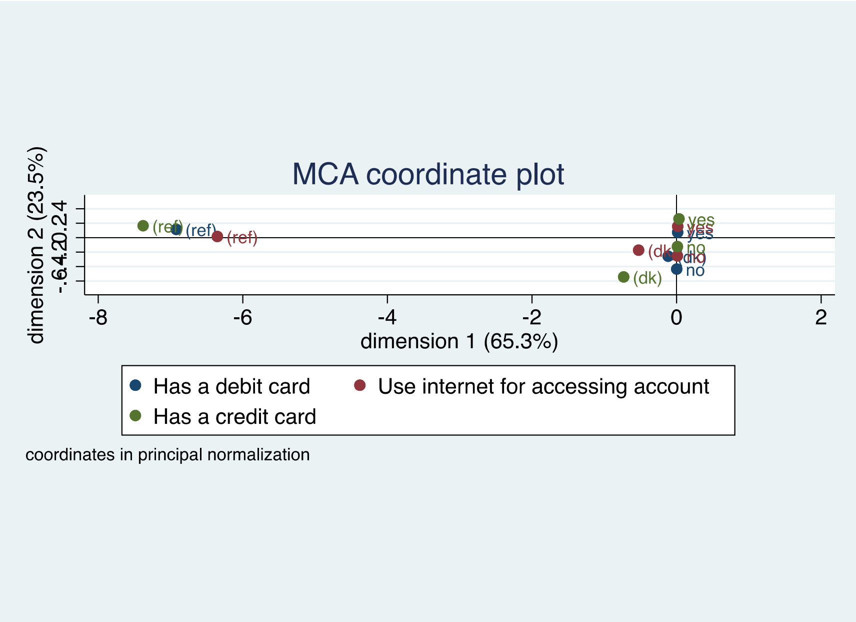
In MCA, the Burt matrix or indicator matrix artificially inflates the chi-square distances between profiles and the total inertia (Gower 2006). Joint correspondence analysis (JCA) can eliminate this inflation of the total inertia by the block diagonal submatrices of the Burt matrix. We use MCA of the Burt matrix for three categorical variables, namely, ownership of debit card, ownership of credit card and use of internet to access account by considering scale adjustments with the principal normalization, which scales the coordinates by the principal inertias. Principal normalization does allow studying the row categories or column categories separately from each other.

5.2 Components of access to finance

Access to finance is mostly a supply side phenomenon and constructed conventionally by taking number of bank branches, availability of automated teller machine (ATM) per 100000 adults at the country level. In this study, we have used demand side indicators like bank account ownership, ownership of debit or credit card by a person with age 15 and above to measure access to finance. In addition, any type of barrier like distance of a formal financial institution from residence, lack of the necessary documentation, affordability and lack of trust in the formal financial system are considered as components of access to formal financial services.

Figure 1 shows the data association for 2021 between 3 components of access to finance: ownership of debit card, credit card and internet access for financial transactions. It displays chi-square distances, and distances between points describing qualitative differences. The origin is the center of gravity of the point-cloud indicating the location that represents the average response. The main axis is the horizontal one, in which the different questions are spread around the center. Responses that indicate having financial access of some kind are clustered around the centre, while no responses are clustered on the left-hand side. This principal, horizontal axis helps explain about 63.3 percent of the variation in the data. On the other hand, the second principal axis explains an additional 23.5 percent of the variation, and is less relevant for our analysis. A clear pattern is seen in the plot. Results from questions on ownership of debit card, credit card and internet access for financial transactions are clustered together.

Figure 1 Components of access to finance in poor European countries: 2021



Source: Global Findex 2021

In MCA, the principal inertias are the squares of the singular values. The principal inertia of the first dimension of access to finance for the whole sample in 2021 is found to be .034 capturing 98 per cent of the total variation in the data. In 2011, the principal inertia of the first dimension of access to finance as .23 explaining 94 per cent of the variation in the sample.

Table 2 Access indicators of financial inclusion

	Principal inertia			
	2011		2021	
Albania	0.21	(97.21)	0.06	(97.84)
Armenia	0.13	(89.14)	0.05	(99.69)
Bulgaria	0.22	(90.72)	0.02	(92.80)
Bosnia	0.19	(94.63)	0.04	(99.35)
Georgia	0.16	(89.39)	0.03	(76.80)
Greece	0.09	(97.23)	0.02	(94.36)
Croatia	0.11	(83.88)	0.04	(99.68)
Hungary	0.22	(86.74)	0.01	(98.84)
Kazakhstan	0.30	(89.27)	0.02	(90.06)
Latvia	0.15	(74.45)	0.01	(78.36)

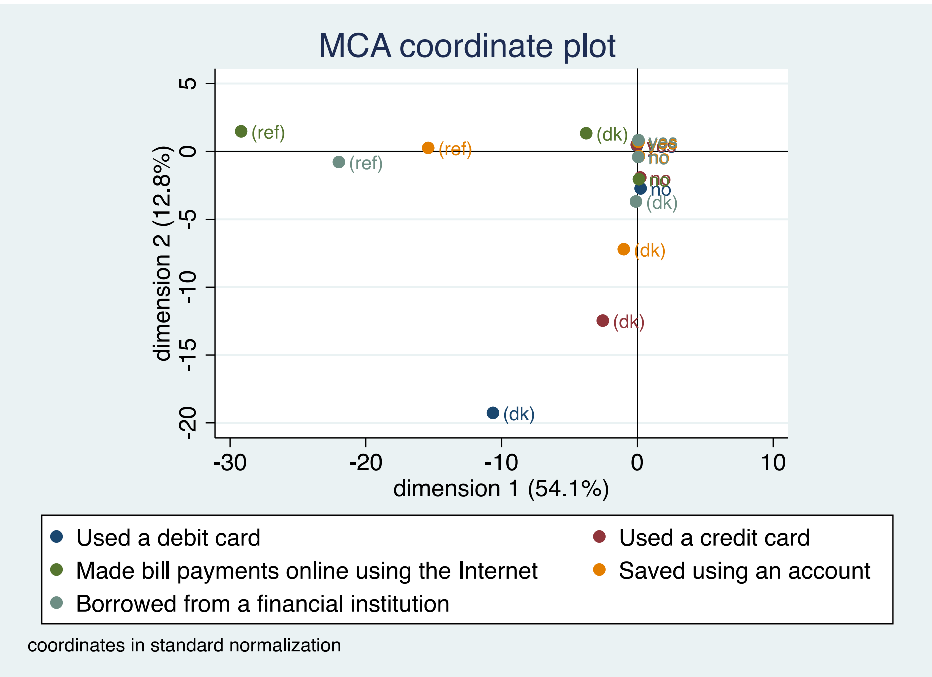
Moldova	0.17	(86.91)	0.00	(71.13)
Romania			0.02	(97.07)
Russia	0.10	(85.3)	0.03	(99.05)
Serbia	0.21	(98.22)	0.03	(98.55)
Turkey	0.68	(98.86)	0.06	(96.05)
Ukraine	0.27	(96.28)	0.02	(86.37)
All	0.23	(93.91)	0.03	(98.41)

Note: Figures shown in parentheses are percentage contribution
Source: AS for Table 1

5.3 Use indicators of finance

Use of financial services is basically demand side indicators which are available in the Global Findex data. We measure use dimension of financial services by taking the use of savings account in making and receive payments, use of debit or credit card, taking loan or not by a person. The use indicator is built to account for people using at least one formal financial service that allow to make money deposit or receive wage, or payment of loan, utility bills, or school fees.

Figure 2 Components of use of finance in poor European countries: 2021



Source: As for Figure 1

Table 3 Use indicators of financial inclusion

	Principal inertia			
	2011		2021	
Albania	0.03	(90.68)	0.04	(72.83)
Armenia	0.01	(75)	0.03	(58.7)
Bulgaria	0.03	(85.98)	0.02	(78.36)
Bosnia	0.03	(87.54)	0.03	(72.37)
Georgia	0.02	(41.59)	0.04	(78.14)
Greece	0.01	(73.87)	0.01	(84.32)
Croatia	0.03	(88.35)	0.01	(83.9)
Hungary	0.01	(64.56)	0.01	(87.61)
Kazakhstan	0.00	(96.67)	0.02	(80.97)
Latvia	0.01	(77.04)	0.00	(56.95)
Moldova	0.02	(94.35)	0.01	(59.16)
Romania			0.02	(81.87)
Russia	0.02	(78.55)	0.01	(66.07)
Serbia	0.00	(88.01)	0.01	(86.02)
Turkey	0.01	(99.94)	0.01	(59.38)
Ukraine	0.01	(97.97)	0.03	(78.06)
All	0.01	(93.93)	0.01	(73.3)

Note: Figures shown in parentheses are percentage contribution
Source: As for Table 1

5.4 Financial inclusion index

Financial inclusion index computed in this study by applying correspondence analysis is roughly similar to the index developed by Park and Mercado (2018). Mean individual scores of financial inclusions by country are shown in Table 4. Higher score represents higher financial inclusion for the respective individual. Inclusiveness of financial services was very poor in Latvia, Croatia, Hungary, Turkey and Greece in 2011. However, the intensity of financial inclusion improved in each sample country in 2021. At the country level, the intensity of financial inclusion is clustered at countries' income levels, with low-income countries at lower financial inclusion scores, and high-income countries at higher levels of financial inclusion.

Table 4 Financial inclusion index

	Mean score			
	2011		2021	
Albania	0.30	(1.02)	1.65	(0.62)
Armenia	0.21	(1.20)	1.33	(0.91)
Bulgaria	0.05	(1.02)	0.70	(1.11)
Bosnia	-0.06	(1.12)	1.07	(1.00)
Georgia	0.25	(1.05)	1.04	(1.08)
Greece	-0.18	(0.98)	0.06	(0.99)
Croatia	-0.73	(1.15)	0.39	(1.12)
Hungary	-0.58	(1.24)	0.19	(1.06)
Kazakhstan	0.05	(1.22)	0.42	(1.28)
Latvia	-1.03	(1.19)	-0.26	(0.86)
Moldova	0.52	(0.88)	1.13	(1.00)
Romania			0.82	(1.11)
Russia	0.07	(1.06)	0.22	(1.15)
Serbia	-0.12	(1.17)	0.83	(1.10)
Turkey	-0.27	(1.16)	0.57	(1.34)
Ukraine	0.14	(1.11)	0.33	(1.28)
All	-0.08	(1.17)	0.63	(1.19)

Note: Figures shown in parenthesis are standard errors
Source: As for Table 1

5.5 Inequality in financial inclusion

We use financial inclusion index scores of adults which are calculated from Global Findex micro level data for 2011 and 2021 in measuring Theil's T inequality index of financial inclusion. Theil's T index is the entropy class of inequality index at $\alpha = 1$ and it gives an inequality by the extent to which an actual society deviates from a perfectly equal society:

$$GE(1) = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{\bar{y}}\ln\left(\frac{y_i}{\bar{y}}\right)$$

It is based on computing for everyone the ratio of their score to the population share. A zero value of the index indicates perfect equality, with higher values of the index indicating greater inequality. Theil's T index (GE(1)) is additively decomposed into within group and between group components.

Table 5 displays Theil's T index of financial inclusion scores in the sample countries in 2011 and 2021. Inequality in financial inclusion increased significantly during this period in every country in this study and is driven mainly by within group component. Inequality in inclusion scores was very high in Latvia followed by Hungary and Greece. Financial inclusion was the least unequal in Albania in 2021.

Table 5 Inequality in financial inclusion: Theil's T index

	2011	2021
Albania	0.03	0.04
Armenia	0.02	0.07
Bulgaria	0.04	0.22
Bosnia	0.06	0.15
Georgia	0.04	0.11
Greece	0.08	0.29
Croatia	0.07	0.25
Hungary	0.04	0.34
Kazakhstan	0.02	0.21
Latvia	0.04	0.59
Moldova	0.02	0.12
Romania		0.20
Russia	0.06	0.26
Serbia	0.06	0.21
Turkey	0.00	0.15
Ukraine	0.04	0.23
All	0.043	0.18
Within group	0.038	0.16
Between group	0.004	0.02

Source: As for Table 1

5.6 Factors explaining inclusion

By taking financial inclusion index score calculated from Global Findex data 2021 for 15 poorest European countries as a dependent variable (y_i), we have estimated financial inclusion function as given below:

$$y_i = \beta_0 + \beta_1 age_i + \sum_{j=1}^{2} \gamma_j D_{ji}^{edu} + \sum_{k=1}^{4} \delta_k D_{ki}^{inc} + \theta D_i^{emp} + \mu D_i^{sex} + \pi D_i^{sector} + \varepsilon_i$$

In Fidex database education of the respondent is a categorical variable with primary, secondary and tertiary level of education. We have used 2 education dummies by taking primary level as a base category. Income of a respondent is given in 5 quantiles, and 4 income dummies are used by taking poorest 20 per cent group as a base category. Employment status is given in the form of employed or out of the workforce. Female is taken as a reference group in the sex dummy. Rural sector is considered as a reference for sectoral dummy. OLS is used for estimation and the estimated coefficients are shown in Table 6.

Table 6 OLS estimation of inclusion function

Factors	Estimated coefficients	
age	0.01	(17.71)
Education dummy		
Secondary school	-0.33	(-8.69)
Tertiary education or more	-0.89	(-20.08)
Income quantile		
Second 20%	-0.14	(-2.93)
Middle 20%	-0.20	(-4.54)
Fourth 20%	-0.25	(-5.6)
Richest 20%	-0.32	(-7.28)
Employment dummy		
out of the workforce	0.44	(15.17)
Sex dummy		
male	0.05	(1.86)
Sector dummy		
Urban	-0.11	(-3.87)
Constant	0.95	(15.54)
Number of observation	4,928	
F(12, 4915)	152.78	
Prob > F	0.00	
R-squared	0.272	
Adj R-squared	0.270	

Note: Figures in parentheses indicate t statistic
Source: Author’s estimation using micro level data from Global Findex 2021

6. Conclusions

We find a strong association between inequality in financial access and income inequality after controlling for a set of structural and policy determinants of income inequality. The study observes that economically vulnerable populations are significantly less likely to be financially included. Households with higher levels of financial literacy are more likely to save and less likely to borrow from informal sources. Inequality in financial access and gender gaps in financial inclusion affect income inequality directly through enabling economic participation, providing access to productive tools, and helping to improve economies of scale. This study observes that financial inclusion is more powerful in alleviating income inequality in the East European countries.

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