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Which Financial Inclusion Indicators and Dimensions Matter for Income Inequality? A Bayesian Model Averaging Approach

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Rogelio Mercado Jr.
The SEACEN Centre

Victor Pontines
The SEACEN Centre
CAMA, Crawford, ANU, Australia

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Keywords

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JEL Classification

C11, C52, O15, O16

Address for correspondence:

(E) cama.admin@anu.edu.au

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*Corresponding author; Senior Economist, The SEACEN Centre; **Senior Economist, The SEACEN Centre; and Research Associate at the Centre for Macroeconomic Analysis (CAMA), ANU and the Globalization Institute, Federal Reserve Bank of Dallas. The authors thank Ole Rummel for his comments and suggestions. The views expressed in this paper are those of the authors and do not necessarily represent those of SEACEN, its member central banks/monetary authorities, CAMA-ANU and the Globalization Institute.

I. Introduction

The impact of financial inclusion on income inequality has been studied from various angles. The within-country analysis of Turegano and Garcia Herrero (2018) suggest that financial inclusion contributes to reducing income inequality to a significant degree. Using cross-country micro-level data and controlling for a wide set of structural and policy determinants of income inequality, Aslan et al. (2017) show that unequal financial access, both overall and between men and women, is significantly and robustly related to greater income inequality at the country level. Using cross-country analysis and controlling for common determinants of income inequality, Park and Mercado (2021a) find that financial inclusion reduces income inequality for middle-income countries but increases it for high-income countries. In an earlier study, Honohan (2007) provides evidence on the negative covariation between income inequality and financial access, given other covariates of income inequality. These studies provide empirical support on the importance of financial inclusion in lowering income inequality, particularly across country income groups. However, these studies use varying measures of financial inclusion as well as its different dimensions.[1] Not only do these papers differ in their use of financial inclusion indices and dimensions, but they also differ on the regressors they use for income inequality.[2] Hence, although these papers provide similar results, their findings were derived from different financial inclusion measures and different determinants of income inequality.

Given the use of different financial inclusion indicators and dimensions, as well as income inequality determinants, there is a need to assess empirically the importance of these indicators as the observed relationship between various financial inclusion indicators and dimensions and income inequality might be due to a few selected indicators, dimensions, and other determinants. Moreover, although several theoretical models are proposed in the literature describing the relationship between finance and income inequality, such as Galor and Zeira (1993), the theoretical foundations examining the link between financial inclusion and income inequality has only grown fairly recently (Barajas et al., 2013; Dabla-Norris et al., 2021; and Park and Mercado, 2021a). Consequently, there is a need to investigate the robustness of the significance of financial inclusion indicators and dimensions as well as other determinants of income inequality in a regression model. This is the primary task of this paper. Specifically, this paper asks: *which financial inclusion indicators and dimensions robustly explain income inequality*? Put differently, which financial inclusion indicators and dimensions must at least be included in a regression model pertaining to the relationship between financial inclusion and income inequality.

The focus on the impact of financial inclusion on income inequality warrants justifications. First, empirical evidence indicates that the impact of financial inclusion on income inequality can differ depending on whether one is considering within- or cross-country income inequality. Cihak and Sahay (2020) find that the benefits of greater financial access and usage are greater for low-income households. In contrast, Park and Mercado (2021a) show that financial inclusion lowers income inequality for middle-income countries but increases it for high-income groups. Second, financial inclusion can either increase or decrease income inequality depending on a country's stage of

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[1] For instance, Honohan (2007 and 2008) constructed a financial access indicator that captures the fraction of the adult population in each economy with access to formal financial intermediaries. Sarma (2008 and 2012) proposed that financial inclusion is a multidimensional concept which comprises measures of access, availability, and usage. Camara and Tuesta (2014) also considered multidimensional aspects of financial inclusion using principal component analysis of usage, access, and barrier measures, while Amidžić et al. (2014) constructed a financial inclusion indicator as a composite indicator of multiple dimensions including outreach, usage, and quality. Park and Mercado (2021b) later considered four dimensions in their financial inclusion including usage, access, financial infrastructure, and financial development.

[2] For example, Aslan et al. (2017) included structural determinants such as level of economic development, and policy variables including trade openness, quality of macroeconomic management, and level of infrastructure. Park and Mercado (2021b) included educational attainment, size of labour force, demographic characteristic, and trade openness in their empirical specification of income inequality on financial inclusion index and dimensions.

economic development. Considering the split between high and low country income groups reflects differences in stages of economic development, in line with the Kuznets curve, as well as varying country characteristics in cross-sectional specification. In this context, Park and Mercado (2021b) provide empirical evidence on the varying significance of financial inclusion dimensions and selected determinants of income inequality by splitting the sample across country income groups. Third, the impact of financial development, including financial inclusion, would have intensive and extensive margins which could give rise to increasing or decreasing income inequality (Cihak and Sahay, 2020). If more low-income individuals and/or households have access to financial services given greater financial inclusion, then a country's income inequality will go down. There is then an extensive impact of financial inclusion on income inequality. In contrast, if financial frictions and financial barriers continue to exist such that only high-income individuals and/or household benefit from greater access to financial services, then greater financial inclusion will reinforce a country's income inequality, in which case, the intensive impact of financial inclusion on income inequality dominates. Consequently, the focus on assessing the robustness of which financial inclusion indicators and dimensions in explaining income inequality is important, given varying aspects for which income inequality is considered (either household or cross-country), differences in the stages of economic development (high or low country income groups), and extensive or intensive impacts.

To address the question in this paper, we employ the Bayesian Model Averaging (BMA) approach, proposed by Raftery et al., (1997), to evaluate which financial inclusion indicators and dimensions, as well as other determinants of income inequality truly matter. The Bayesian model averaging addresses model uncertainty given our lack of knowledge on the true empirical model, which is inherent in any classical regression model, including cross-country regressions such as those employed in this paper.[3] Specifically, the posterior inclusion probability (PIP) derived from BMA will inform us on the probability or likelihood that a given variable (whether it be a financial inclusion indicator, dimension, or other determinant) should at least be included in an empirical model of income inequality, i.e., higher PIP values suggest greater probability of including specific variables in an empirical model of income inequality. Unlike the cross-sectional ordinary least squares (OLS) regression which determines the significance of a specific regressor, BMA informs us of the probability that a regressor should at least be included in a certain empirical specification of income inequality, given model uncertainty. The use of Bayesian model averaging to identify key financial inclusion indicators, dimensions, and other determinants of income inequality differentiates this paper from other empirical papers which consider the classical statistical significance of regressors on a dependent variable, such as Honohan (2007, 2008), and Park and Mercado (2018, 2021a, and 2021b).

This paper proceed as follows. We assemble a dataset for 116 high- and low-income countries grouped using the World Bank country income classification (2022). The dataset includes a measure of income inequality, various financial inclusion indicators and dimensions grouped into access, usage, and depth; as well as determinants of income inequality such as education completion, labour force, demographic feature, and trade openness. Each financial inclusion dimension includes at least seven indicators. In total, we assess 21 financial inclusion indicators alongside four standard determinants of income inequality. We then proceed with Bayesian model averaging using Hasan et al. (2018), Fedlkircher and Zeugner (2009) and Fernandez et al. (2001) prior selections and a standard "birth-death sampler" for our sampling method. The results show that three financial inclusion access indicators (number of commercial bank branches and automated teller machines (ATMs) and having a financial institution account to receive wages), and three financial inclusion usage indicators (made a withdrawal, savings, and receiving wages) have PIP values greater than 0.65, implying an almost two-thirds probability that these indicators should be included in a model assessing the significance of financial inclusion indicators for income inequality. However, these results only hold for our low-

[3] Bayesian model averaging has been widely used in the empirical literature including Fernandez et al. (2001) in the context of economic growth and Hasan et al. (2018) on finance and growth nexus.

income country group, which includes middle low-income and low-income countries, but not for our high-income group, which includes high- and middle high-income countries. In terms of dimensions, the aggregate measure of financial inclusion access has PIP values of more than 0.65, whereas the aggregate measure of financial usage has PIP values of greater than 0.5. Interestingly, nowhere in our baseline results and in almost all our robustness tests do we find PIP values higher than 0.65 for any of our financial depth indicators as well as dimension.[4] Among the determinants of income inequality, demographic characteristic, proxied by median age, have PIP values greater than 0.75 for both country income groups. These results hold against a battery of sensitivity tests.

These findings contribute to the existing literature on financial inclusion and income inequality in several ways. First, in constructing financial inclusion measures and assessing the importance of financial inclusion dimensions on income inequality, financial access and usage are the two key dimensions that must be considered in any empirical exercise. Second, in developing theoretical models in explaining the link between financial inclusion and income inequality, focus must be given on household or country heterogeneities in financial access and usage in theoretical model set-ups. The same focus on financial access and usage should considered for empirical cross-country analysis.

This paper proceeds as follows. In the next section we discuss financial inclusion and income inequality and provide some stylised facts. Section 3 presents the Bayesian model averaging and our empirical specification. Section 4 discusses our main findings and sensitivity tests, while the last section provides concluding remarks.

II. Financial Inclusion and Income Inequality

Cross-country income inequality has been decreasing over the past decades, mainly due to rapid economic growth and poverty reduction in emerging and developing economies. However, within-country income inequality has been rising, more so in advanced economies where almost half witnessed an increase in income inequality over the past two decades (Cihak and Sahay, 2020). Several studies have provided theoretical foundations linking financial inclusion or financial development, in general, with income inequality. For instance, Park and Mercado (2021b) used the model of Dabla-Norris et al. (2021) and extended it in the context of financial inclusion and socioeconomic outcomes including income inequality. In the model, economic agents (individuals) differ in their initial wealth and managerial skills or productivity. They decide whether to become a worker or an entrepreneur by comparing the payoffs that they will earn from these activities. Entrepreneurship can be profitable but only after upfront expenditures have been covered, and the profitability will depend on the individual's talent.

Given financial frictions in the model, four types of agents emerge, namely unconstrained workers, constrained workers, constrained entrepreneurs, and unconstrained entrepreneurs.[5] With the introduction of credit (financial inclusion), talented individuals can invest the required capital and become entrepreneurs, thereby shrinking the share of workers, and increasing the share of entrepreneurs. Credit, likewise, enables entrepreneurs to raise their production to the optimal level. These mechanics lead to greater economic output and lower poverty. But given the model set-up and mechanics, there could be ambiguous impact on income inequality, depending on the intensive and extensive margins (Cihak and Sahay, 2020).

[4] To consider only those variables that truly matter for income inequality, we set a strict PIP threshold value of 0.65, such that only those variables that have close to two-thirds probability will be included in the true model. Furthermore, in our empirical analysis using the BMA, it is at least at this value of the PIP where we find that almost all our respective variables have posterior means that are larger than their posterior standard deviations.

[5] Financial frictions include costly access to credit, collateral constraints, and inefficient financial systems. These financial frictions lead to financial exclusion, which exacerbates poverty traps and income inequality (Galor and Zeira, 1993).

As credit access improves, more low-income households can become entrepreneurs and thereby lowering income inequality (extensive margin). On the other hand, improving financial access and reducing financial frictions will enhance financial services for high-income households, thereby increasing income inequality (intensive margin). In a cross-country setting, economies differ in the initial proportion of agents who are constrained and unconstrained. For high-income economies, it is expected that the proportion of unconstrained agents is greater than constrained agents, whereas the converse is true for low-income economies. Moreover, economies also differ on which financial frictions exist as well as the degree and persistence of these frictions. Such differences in initial conditions and financial frictions explain the varying significance and impacts of financial inclusion on income inequality. Consequently, assessing the extensive and intensive impacts of financial inclusion on income inequality across high and low-income groups is warranted and considered in this paper.[6]

To contextualise the relationship between financial inclusion and income inequality, **Figures 1, 2, and 3** present the scatter plots for the income inequality measure and the three financial inclusion dimension measures namely, access, usage, and financial depth. The income inequality measure is the ratio between the top 10% of income group and bottom 50% income group, sourced from the World Inequality Database. As it is difficult to use the Gini index, which is based on household survey data, the World Inequality Database offers an alternative source of income inequality measure that is available for a larger set of economies on an annual basis. We take the average annual value of our income inequality measure from 2016 to 2021 and plot these with the average financial inclusion dimension measures from 2010-2015. The financial inclusion dimension indices are computed as simple or unweighted averages of various indicators that fall into each dimension. For financial access, seven indicators are included, namely, financial institution account, credit card ownership, debit card ownership, ownership of either credit or debit card, number of commercial bank branches, number of automated teller machines, and financial account used to receive wages. For financial usage, withdrawal, savings, receiving wages, and borrowings from financial account and made and/or received digital payments are included. For financial depth, domestic credit provided to the private sector, domestic credit provided by banks, financial system deposits, bank assets, insurance company assets, bank deposits, and stock market capitalisation are included. These indicators are sourced from various datasets, with Appendix 2 providing data sources and notes. In total, the sample includes 116 countries divided between high- and low-income groups. The high-income group includes 72 countries which are classified as high-income and upper middle-income countries by the World Bank. The low-income group includes 44 countries which are classified as lower middle-income and low-income countries by the World Bank.

Figure 1 shows the negative relationship between financial access and income inequality, such that economies with higher financial access tend to have lower income inequality. The same relationship holds for **Figure 2** which shows that economies with higher financial usage tend to have lower income inequality. The same linear fit is noted in **Figure 3** for income inequality and financial depth. However, notice the presence of several outliers in the figures such as Hong Kong, China and United Kingdom which are financial centres. In summary, the scatter plots for income inequality and financial access, usage, and, to some extent, financial depth show the inverse relationship between an aggregate measure of income inequality and the three financial inclusion dimensions.

[6] Refer to Section III.B for discussion on empirical specification.

III. Empirical Approach

A. Bayesian Model Averaging[7]

Previous studies, including Raftery (1997) and Hoeting et al. (1999), show that ignoring model uncertainty leads to exaggerated inference in statistical estimates. Bayesian model averaging (BMA) is a method that accounts for model uncertainty, which explains its growing application in applied empirical studies. BMA addresses model uncertainty by conducting Bayesian inference on a weighted average of all potential combinations of regressors. In Bayesian econometrics, these weights arise naturally as posterior model probabilities (PMPs).

In a traditional linear regression model, such as:

$$y_i = \alpha + X_i\beta + \varepsilon_i \qquad\qquad \varepsilon \sim N(0, \sigma^2 I) \tag{1}$$

where y is a dependent variable, α is a constant, X is the matrix containing the explanatory variables, β the corresponding coefficients, and ε is a vector of normally distributed independent and identically distributed (IID) error term with variance σ^2. The source of the model uncertainty comes from the selection of regressors to include in the right-hand side of equation (1), such as in the case of income inequality determinants. When the true regression model is unknown, estimation typically begins by including all the regressors in the model, and then sequentially omitting insignificant regressors based on classical statistical significance tests to arrive at a best model or a limited number of preferred models. As shown, inter alia, Koop (2003), using this strategy, the probability of committing the mistake of retaining an unimportant variable or omitting a relevant variable increases with the number of sequences of regressions conducted.

BMA, on the other hand, would take all possible combinations of the regressors in X and construct a weighted average of the coefficients. If X contains K potential regressors, the total number of models in X is 2^K such that we have $M_1, \dots, M_i$, where $i \in [1, 2^K]$. The weights used for the averaging of the model coefficients across the sub-models is called the posterior model probabilities (PMPs), which arise from Bayes' theorem:

$$p(M_i \mid y, X) = \frac{p(y \mid M_i, X)\, p(M_i)}{p(y \mid X)} \tag{2}$$

where $p(y|M_i, X)$ is the marginal likelihood of each sub-model (i.e., the probability of the data given the model M_i), $p(M_i)$ is the prior model probability (i.e., how probable a sub-model is regarded by the researcher before looking at the data) and $p(y|X)$ is the integrated likelihood. The integrated likelihood is typically omitted due to it being constant over all sub-models. In doing so, the PMPs become directly proportional to the marginal likelihood and the prior model probability, which is expressed as:

$$p(M_i \mid y, X) \propto p(y \mid M_i, X)\, p(M_i) \tag{3}$$

Following from the PMPs above, the full posterior distribution of the coefficients can be calculated as a weighted average of the posterior distributions under each sub-model, where the weights are given by the PMPs:

[7] The discussion in this section draws from various sources, including Feldkircher and Zeugner (2009), Moral-Benito (2015), Hasan et al. (2018) and Zeugner (2022). See these studies for further details on the method of Bayesian model averaging.

$$p(\beta \mid y, X) = \sum_{i=1}^{2^K} p(\beta_i \mid M_i, y, X) p(M_i \mid y, X) \qquad (4)$$

where $p(\beta_i|M_i, y, X)$ is the posterior distribution of the coefficients under each sub-model. Equation (4) provides inference about the coefficients that considers model uncertainty. From this equation, one can also calculate posterior means and standard deviations to arrive at point estimates of the coefficients and their associated standard deviations. Finally, and more importantly for our study on income inequality and financial inclusion, is the calculation of the posterior inclusion probability (PIP), which is a standard metric that is always reported in every applied work that employs BMA. The PIP represents the probability that a particular regressor k is included in all the sub-models considered. It is calculated as the sum of the PMPs of the models that include this regressor k. A PIP value of 0.90 means that a given variable has 90% probability of being included in the true model, whereas a PIP value of 0.10 means that a variable has only 10% probability of being included in the true model. Hence, higher PIP values imply greater importance of selected variables in a model.[8]

In applying Bayesian inference for Equation 1, priors need to be elicited for the *parameters* of each model and for the *model* itself, $p(M_i)$. The PMPs crucially depend on the choice of the priors as shown in equations (2) and (3). Two types of priors are discussed in turn. We set a conditional prior for the coefficients of the i-th sub-model with a mean of zero and the variance structure proposed by Zellner (1986). This variance structure is referred to as the Zellner g, defined as $g(X_i'X_i)^{-1}$, where $(X_i'X_i)^{-1}$ is the posterior variance arising from the sample of regressors included in the i-th sub-model. The hyperparameter g reflects the uncertainty on whether the coefficients in the i-th sub-model are indeed zero. In our baseline estimations, following Hasan et al. (2018) and Feldkircher and Zeugner (2009), we use two flexible prior settings for g: first, we estimate a separate g for each sub-model, which is also known as a local empirical Bayes estimate of g [9]; and the second is referred to as the hyper- g, where the shrinkage factor of the form, $\frac{g}{1+g}$, is a Beta distribution with a mean equal to $\frac{2}{a}$, where $a \in$ (2,4] based on Liang et al. (2008). In our baseline, we set a equal to 3. We check the robustness of our results by using the standard unit information prior (UIP) where we set g to be equal to N as well as by a based on Feldkircher and Zeugner.[10] [11]

In terms of the priors for the model, like Hasan et al. (2018), we follow Fernandez et al. (2001) in setting a uniform model prior in our baseline estimations to also reflect our lack of prior knowledge regarding the "true" model. However, a known limitation of this model prior is that the mass of its distribution is close to the expected model size of $K/2$. In view of this, to check the sensitivity of our baseline results, we also follow Hasan et al. (2018) in setting a binominal-beta hyperprior that is less tight around a particular expected model size.[12]

BMA uses the Metropolis-Hastings algorithm to evaluate the model space. In our baseline estimates, we use the standard birth-death sampler, which proposes candidate models by randomly choosing the regressors. If the proposed regressors are not part of the current model being evaluated, M_i, these regressors are included. However, these are dropped when they are already included in M_i. We check

[8] The empirical analysis discussed in Section IV uses a PIP threshold value of 0.65 to differentiate relevant variables from those that are not. This is comparatively a high threshold value as Hasan et al. (2018) used a threshold PIP value of only 0.50 in their study of economic growth and financial depth. Our choice is dictated by the fact that, in addition to having at least two-thirds probability of being included in the model as being a relevant variable, in almost all of our empirical results that follow, it is at least at this PIP value where the posterior means of the respective variables are larger than their posterior standard deviations.

[9] For further discussion on this local empirical Bayes estimate of g, refer, for instance, to Liang et al. (2008).

[10] Hasan et al. (2018) used the UIP prior in their robustness tests.

[11] Specifically, we set a equal to $2 + 2/K^2$ and $2 + 2/N^2$.

[12] For further discussion on this model prior, refer to Ley and Steel (2009).

the sensitivity of our baseline by using the reversible-jump sampler, which attaches a 50% probability to the next candidate model chosen by the birth-death sampler. Also with 50% probability, this sampler randomly swaps one of the regressors in M_i for another regressor that is not included in M_i.

B. Empirical Specification

In applying Bayesian model averaging in the context of income inequality and financial inclusion, we employ Bayesian inference for Equation 1.[13] *Y* pertains to a measure of income inequality and *X* includes explanatory variables viz. individual indicators of financial inclusion and determinants of income inequality such as educational attainment, trade openness, median age, and labour force participation (Cihak and Sahay 2020; Furceri and Ostry 2019; Park and Mercado 2021a and 2021b; and Paweenawat and McNown 2014). We then estimate equation 1 using aggregate measures of the three financial inclusion dimensions, namely, financial access, financial usage, and financial depth, where each dimension is a linear combination of individual financial inclusion indicators using simple average (unweighted average).[14]

Our empirical specification utilises cross-country measures of income inequality as well as the above mentioned regressors, particularly financial inclusion indicators and dimensions. The sample includes 116 countries divided between high- and low-income groups. The high-income group includes 72 countries which are classified as high-income and upper middle-income countries by the World Bank. The low-income group includes 44 countries which are classified as lower middle-income and low-income countries by the World Bank. We estimate equation 1 for both country income groups. The split between high- and low-income groups reflects the varying developmental stages of each group which would matter in determining whether financial inclusion reduces or increases income inequality or if at all. To address endogeneity, we take the average value of our income inequality measure for country *i* from 2016-2021 and use the average values of financial inclusion indicators and dimensions as well as other determinants of income inequality for country *i* from 2010-2015, whenever data is available for that period. Technically, we are estimating the current average values of income inequality on lagged average values of the regressors.

Table 1 presents the descriptive statistics of all variables included in our Bayesian model.[15] The table shows that income inequality is higher for low-income countries, compared to high-income countries. In contrast, the latter have substantially higher values of financial inclusion indicators and dimensions compared to low-income countries.

IV. Empirical Results and Analysis

A. Baseline Results

Tables 2 and 3 present our baseline results in which the various financial inclusion indicators and the other determinants of income inequality are included in the estimation of the BMA. **Table 2** presents the results for our low-income country group, while Table 3 shows the results for the high-income country group. Both tables contain two columns where each column is distinguished by our chosen prior for the parameters. Specifically, column (1) uses a local empirical Bayes estimate of the hyperprior *g*, while column (2) sets a value of 3 for the *a* in the mean of the Beta distribution to determine *g*.[16] Each column reports the values of the PIP, posterior mean, and the posterior standard

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[13] In conducting our Bayesian model averaging, we use the R package BMS created by Martin Feldkircher and Stefan Zeugner.
[14] We also used principal component analysis to linearly combined individual financial inclusion indicators by dimension in our sensitivity tests.
[15] The country sample grouping is presented in Appendix 1 while Appendix 2 presents data sources and notes.
[16] In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.

deviation in this order. Column (1) of Table 2 indicates that three financial inclusion usage indicators named, respectively, as *saved at a financial institution*, *made a withdrawal*, *received wages in a financial institution account,* and three financial inclusion access indicators named as *commercial bank branches*, *automated teller machines* and *account used to receive wages* have PIP values higher than 0.65.[17] In addition, these variables have posterior means that are larger than their respective posterior standard deviations. The same findings are attributed to two standard determinants of income inequality, namely, *median age* and *labour force ratio* whereby both variables have PIP values larger than our set PIP threshold of 0.65 as well as having posterior means higher than their posterior standard deviations. It is noteworthy to mention that three financial inclusion indicators, *made a digital payment* (usage indicator), *owns a debit card* (access), and *domestic credit to private sector* (depth) have PIP values greater than 0.50 but below our threshold of 0.65.[18]

Column (2) of Table 2 depicts results that are very much identical to the ones presented in column (1). Setting a different prior to determine the hyperprior *g*, in addition to posterior means higher than their posterior standard deviations, we again obtain PIP values greater than 0.65 for the three financial inclusion usage indicators (made a withdrawal, saved at a financial institution, and received wages in a financial institution account) and three access indicators (number of commercial bank branches, ATMs and having a financial institution account to receive wages). The same holds for the two standard determinants of income inequality, i.e., median age and labour force ratio. Also similar to column (1), the three financial inclusion indicators, namely, made a digital payment, owns a debit card and domestic credit to private sector have PIP values between 0.50 and 0.65, although their respective posterior means are smaller compared to the posterior standard deviations.

However, when we conduct the BMA exclusively for our sample of high-income countries shown in **Table 3**, almost all our above noted findings now disappear. Comparing the results from both columns of Table 3 to the ones previously highlighted in Table 2, we observe that the demographic characteristic named median age is the lone variable with a PIP value greater than 0.65. All the six financial inclusion indicators (the three usage and three access indicators) that mattered exclusively for our sample of low-income countries presented in Table 2, now become unimportant in view of PIP values that are below 0.65, indeed even smaller than 0.50. Nonetheless, two financial indicators, namely, made or received a digital payment and saved at a financial institution in both columns of Table 3 have PIP values that are between 0.50 and 0.65. However, their posterior means are smaller than their posterior standard deviations.

Turning to our baseline results using the three financial inclusion dimensions, namely, financial access, financial usage, and financial depth, along with the determinants of income equality such as education completion, labour force, median age, and trade openness, the BMS results are presented in **Tables 4 and 5**. **Table 4** presents the results for our sample of low-income countries, while Table 5 shows the results for the high-income countries. Like Tables 2 and 3, Tables 4 and 5 contain two columns where each column is distinguished by our chosen prior for the parameters. Again, column (1) uses a local empirical Bayes estimate of the hyperprior *g*, while column (2) sets a value of 3 for the *a* in the mean of the Beta distribution to determine *g*.[19] As before, each column reports the values of the PIP, posterior mean, and the posterior standard deviation in this order. Column (1) of Table 4 indicates that among the three financial inclusion dimensions, financial access has a PIP value greater than 0.65. In addition, this value of the PIP has a posterior mean that is larger than its posterior standard deviation. Another dimension, financial usage has a PIP value larger than 0.50 but below 0.65,

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[17] Refer to Appendix Table A2 for the complete definitions of these variables. We italicise variables when we refer to it the first time in the main text.

[18] In addition, these results are limited by the fact that the posterior means of these three variables are smaller than their respective posterior standard deviations.

[19] Again, in both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.

although its posterior mean is smaller relative to its posterior standard deviation. In terms of the other determinants of income inequality, only median age came out with a value of the PIP larger than 0.65.

Column (2) of Table 4 shows results that are very much like the ones presented in column (1). Despite the slight dip in the value of the PIP, but with a posterior mean higher than its posterior standard deviation, financial access shows a PIP value larger than 0.65. Also similar to column (1), financial usage has a PIP value larger than 0.50 but below 0.65, but then again, its posterior mean is smaller compared to its posterior standard deviation. Similarly, median age is the only determinant that shows a PIP value larger than 0.65. Columns (1) and (2) of **Table 5** present our results when we estimate the BMA exclusively for our sample of high-income countries. In this table, we observe that almost all our highlighted findings from Table 4 now disappear. The lone exception is the demographic characteristic, median age which again shows a PIP value greater than 0.65. All the three financial inclusion dimensions registered PIP values below 0.50.

B. Sensitivity Tests

In this sub-section, we assess the robustness of our baseline results by conducting a battery of sensitivity tests. First, we examine the sensitivity of our baseline findings presented in Tables 2 and 3 when we do not split the sample by country income groups. **Table A3** shows the pooled sampled BMA results in which the various financial inclusion indicators and the other determinants of income inequality are included in the estimation. Columns (1) and (2) of Table A3 use the same parameter priors, model priors and the Markov-Chain Monte Carlo (MCMC) sampler as Tables 2 and 3. For instance, in terms of the parameter priors, a local empirical Bayes estimate of the hyperprior g (column 1), and a value of 3 for the a in the mean of the Beta distribution to determine g (column 2) were used. Both columns also use a uniform model prior, and a birth-death sampler to evaluate the model space. Like Tables 2 and 3, the values of the PIP, posterior mean and the posterior standard deviation in this order are reported in both columns of Table A3. The results consistently show that two financial inclusion usage indicators namely, *made or received a digital payment* and *received digital payments* have PIP values that are larger than 0.65. Among the other determinants of income inequality, only median age came out with a PIP value larger than 0.65. The results suggest that by not splitting the sample by country income groups, the estimates will be driven by high-income countries which dominates the sample size. It is thus important to split the sample by country income groups.

Second, we examine the sensitivity of our findings presented in Tables 4 and 5 by pooling high- and low-income country groups together. **Table A4** presents the pooled sample BMA results in which the various financial inclusion indicators are grouped into three dimensions, i.e., financial access, financial usage, and financial depth. The parameter priors, model priors, and MCMC sampler are the same as in Tables 4 and 5. Again, like Tables 4 and 5, the values of the PIP, posterior mean and the posterior standard deviation are reported in both columns of Table A4. The results presented in Table A4 consistently show that financial access and financial usage dimensions have PIP values larger than 0.65, although the latter has a posterior mean that is relatively smaller compared to its posterior standard deviation. Among the other determinants of income inequality, only median age came out with a PIP value larger than 0.65. These results strongly reinforce our baseline results for low-income countries (Table 4), and to a certain extent our findings for high-income countries (Table 5) as well. This implies that by aggregating various financial inclusion indicators into financial inclusion dimensions, our result showing that high-income countries drive the BMA estimates from a pooled sample of countries, is no longer observed.

Third, we conducted another sensitivity test on our results presented in Tables 4 and 5 by varying how we linearly combine the various individual financial inclusion indicators into the three dimensions of financial inclusion. Specifically, instead of using a simple average to linearly combine the individual indicators, we use principal components analysis (PCA).[20] The PCA results are presented in **Tables A5 and A6** for our sample of low-income and high-income countries, respectively. These two tables follow the same presentation as in Table A4. Comparing the estimates in these two tables with those from Tables 4 (low-income countries) and 5 (high-income countries), we note that our baseline results hold. For instance, looking at the sensitivity test results for low-income countries in **Table A5**, both columns consistently indicate that only financial access has a PIP value higher than 0.65. Although, the PIP values of financial usage have risen, their posterior means are still relatively smaller compared to its posterior standard deviations. In terms of the other determinants of income inequality, again only median age came out with a value of the PIP larger than 0.65. As to the robustness test results for high-income countries in **Table A6**, all the three financial inclusion dimensions have PIP values below 0.50. Only median age reported a PIP value higher than 0.65.

Finally, we conducted further tests on our baseline results for low-income countries (Tables 2 and 4) by changing our parameter priors, model priors and the MCMC sampler. The robustness test results are presented in **Tables A7 and A8**. These two tables contain eight columns, and each column pertains to a certain choice of the priors for the parameter and the model as well as the choice of the MCMC sampler. These specific choices in both tables are as follows: In column (1), the prior for the parameter is where a in the mean of the Beta distribution is set equal to $2+2/K^2$ to determine g, where K is the number of regressors. The model prior is uniform, and a birth-death sampler is used to evaluate the model space. In column (2), the prior for the parameter is where a in the mean of the Beta distribution is set equal to $2+2/N$ to determine g, where N is the number of regressors, while the choice of the model prior and the MCMC sampler is similar to column (1). In column (3), the prior for the parameter is a local empirical Bayes estimate of *g, t*he model prior is random and the MCMC sampler is similar to column (1). In column (4), the prior for the parameter is similar to column (3), the model prior is similar to column (1), and a reversible-jump sampler is used to evaluate the model space. In column (5), the prior for the parameter is where a in the mean of the Beta distribution is set equal to 3 to determine *g, t*he model prior and the MCMC sampler is similar to column (3). In column (6), the prior for the parameter is similar to column (5), the model prior is similar to column (1), and the MCMC sampler is similar to column (4). In column (7), the priors for the parameter and the model are similar to column (1), and the MCMC sampler is similar to column (4). In column (8), the prior for the parameter is similar to column (2), the model prior is similar to column (1), and the MCMC sampler is similar to column (4). For the sake of brevity, we only present the PIP values in each column of both tables.[21]

We first examine the robustness test results presented in **Table A7**. We can observe from the robustness test results that our earlier baseline findings (Table 2) either hold or in some cases, we obtain stronger findings. As in our baseline results, the three financial inclusion usage indicators namely, saved at a financial institution, made a withdrawal, received wages in a financial institution account, and the three financial inclusion access indicators namely, commercial bank branches, automated teller machines and account used to receive wages remain to have PIP values higher than 0.65 in all columns. The same goes with the other determinants of income inequality, i.e., median age and labour force ratio. Interestingly, for columns (3) and (5) in Table A7, almost all indicators have PIP values greater than 0.60. In fact, it is only in these specifications where we find stronger results relative to our baseline results, as the PIP values are greater than 0.60. For instance, we find financial depth indicators have significantly higher PIP values compared to the other specifications. Meanwhile, for specifications in columns (1), (2), (4), (6), (7) and (8), our baseline findings hold. Next, we examine the

[20] The seven indicators per dimension were linearly combined using weight derived from principal component analysis. The PCA is a commonly used method combining a set of variables to extract maximum common information from individual indicators. In effect, the PCA partitions the variance in a set of variables and uses it to determine weights that maximise the resulting principal component's variation. The derived principal component is a variable that captures variations in data to the maximum extent possible.

[21] The posterior mean and the posterior standard deviation are available upon request from the authors.

robustness test results in **Table A8**. As shown in Table A8, our baseline findings in Table 4 either hold or yield higher PIP values. Just as in our baseline results, financial access indicators have PIP values larger than 0.65 in all columns. The same holds for the variable median age. It is noteworthy to mention that financial usage indicators have PIP values that are between 0.51 to 0.61 in some of the columns such as columns (3) to (6) in Table A8.

V. Concluding Remarks

In this paper, we assess which financial inclusion indicators, dimensions, and determinants of income inequality truly matter in estimating the significance and impact of financial inclusion on income inequality. Unlike cross-country OLS estimation, we employ Bayesian model averaging (BMA) and used the computed posterior inclusion probability (PIP) values to evaluate which financial inclusion indicators, dimensions, and determinants of income inequality must at least be included or considered in an empirical specification of financial inclusion and income inequality given model uncertainty. The results show that for the low-income country group, three financial access indicators (number of commercial bank branches and ATMs and having a financial institution account to receive wages), and three financial inclusion usage indicators (made a withdrawal, savings, and receiving wages) have PIP values greater than 0.65, implying almost a two-thirds probability that these indicators should at least be included in a model assessing the significance of financial inclusion indicators for income inequality. For financial inclusion dimensions, our results indicate that financial access has PIP values of more than 0.65, whereas financial usage has PIP values of greater than 0.5. Interestingly, nowhere in our baseline results and in almost all our sensitivity checks do we find PIP values higher than 0.65 for any of our financial depth indicators as well as financial depth dimension. Among the determinants of income inequality, demographic characteristic, proxied by median age, have PIP values greater than 0.75.

Our results suggest that in any empirical specification assessing the significance and impact of financial inclusion on income inequality, financial access and usage indicators and dimensions are the relevant factors which must at least be considered. Unfortunately, we find no evidence of the same for financial depth indicators and dimension. More importantly, our findings offer evidence that theoretical models linking financial inclusion and income inequality could focus on the role of financial access and usage by providing theoretical foundations on the mechanics as to how these those two dimensions of financial inclusion impact income inequality. Furthermore, this paper applies BMA on financial inclusion and income inequality. Future studies may consider the same empirical approach in assessing the relationship between financial inclusion indicators and dimensions and a host of other socio-economic outcomes such as poverty, women empowerment, and entrepreneurship.

References

Aslan, Goksu, Corinne Deléchat, Monique Newiak, and Fan Yang. (2017). Inequality in financial inclusion and income inequality. *IMF Working Paper*, No. 17/236. Washington, DC: International Monetary Fund.

Amidžić, Goran, Alexander Massara, and Andre Mialou. (2014). Assessing countries' financial inclusion standing – A new composite index, *IMF Working Paper*, No. 14/36. Washington, DC: International Monetary Fund.

Barajas, Adolfo, Thorsten Beck, Era Dabla-Norris, and Seyed Reza Yousefi. (2013). Too cold, too hot, or just right? Assessing financial sector development across the globe. *IMF Working Paper,* No. 13/81. Washington, DC: International Monetary Fund.

Camara, Noelia, and David Tuesta. (2014). Measuring financial inclusion: A multidimensional index. *bbva research working paper*, 14/26. Madrid: bbva.

Cihak, Martin, and Ratna Sahay. (2020). Finance and inequality, *IMF Staff Discussion Note,* SDN/20/01. Washington, DC: International Monetary Fund.

Dabla-Norris, Era, Yan Ji, Robert M. Townsend, and D. Filiz Unsal. (2021). Distinguishing constraints on financial inclusion and their impact on GDP, TFP, and the distribution of income. *Journal of Monetary Economics,* 117 (c): 1–18.

Feldkircher, M. and Stefan Zeugner. (2009). Benchmark priors revisited: On adaptive shrinkage and the supermodel effect in bayesian model averaging. *IMF Working Paper,* WP/09/202. Washington, DC: International Monetary Fund.

Feldkircher, M. and Stefan Zeugner. (2022). Bayesian model averaging with BMS. Mimeo. http://bms.zeugner.eu.

Fernandez, C., Eduardo Ley, and Mark F.J. Steel. (2001). Model uncertainty in cross-country growth regressions. *Journal of Applied Econometrics*, 16(5): 563-576.

Furceri, Davide, and Jonathan Ostry. (2019). Robust determinants of income inequality. *Oxford Review of Economic Policy,* 35 (3): 490–517.

Galor, Oded, and Joseph Zeira. (1993). Income distribution and macroeconomics. *Review of Economic Studies,* 60: 35–52.

Hasan, Iftekhar, Roman Horvath, and Jan Mares. (2018). What type of finance matters for growth? Bayesian model averaging evidence. *The World Bank Economic Review*, 32(2): 383-409.

Hoeting, Jennifer, David Madigan, Adrian Raftery and Chris Volinsky. (1999). "Bayesian model averaging: A tutorial. *Statistical Science,* 14(4), 382-417.

Honohan, Patrick. (2007). Cross-country variation in household access to financial services. World Bank paper prepared for the conference access to finance, 15−16 March, Washington, DC.

Honohan, Patrick. (2008). Cross-country variation in household access to financial services. *Journal of Banking and Finance,* 32 (11): 2493–500.

Koop, Gary. (2003). Bayesian econometrics. New York: Wiley.

Ley, Eduardo, and Mark F.J. Steel. (2009). On the effects of prior assumptions in bayesian model averaging with application to growth regression. *Journal of Applied Econometrics,* 24: 651-674.

Liang, Feng, Rui Paulo, German Molina, Merlise A. Clyde, and Jim O. Berger. (2008). Mixtures of g priors for Bayesian variable selection. *Journal of the American Statistical Association,* 103: 410-423.

Moral-Benito, Enrique. (2015). Model averaging in economics: An overview. *Journal of Economic Surveys,* 29(1): 46-75.

Park, Cyn-Young, and Rogelio Mercado Jr. (2018). Financial inclusion, poverty, and income inequality. *Singapore Economic Review*, 63 (1): 1–22.

Park, Cyn-Young, and Rogelio Mercado Jr. (2021a). Financial inclusion: new measurement and cross-country impact assessment. In Financial Inclusion in Asia and Beyond: Measurement, Development Gaps, and Economic Consequences, edited by Tony Cavoli and Rashesh Shrestha, 98–128. London: Routledge.

Park, Cyn-Young; Mercado, Rogelio. (2021b). Understanding financial inclusion: What matters and how it matters. *ADBI Working Paper*, No. 1287, Asian Development Bank Institute (ADBI), Tokyo.

Paweenawat, Sasimon Warunsiri, and Robert McNown. (2014). The determinants of income inequality in Thailand: A Synthetic Cohort Analysis. *Journal of Asian Economics*, 31–32: 10–21.

Raftery, Adrian, David Madigan, and Jennifer Hoeting (1997). Bayesian model averaging for linear regression models. *Journal of the American Statistical Association*, 92(437), 179-191.

Sarma, Mandira. (2008). Index of financial inclusion. *Working Paper*, No. 215. New Delhi: Indian Council for Research on International Economic Relations.

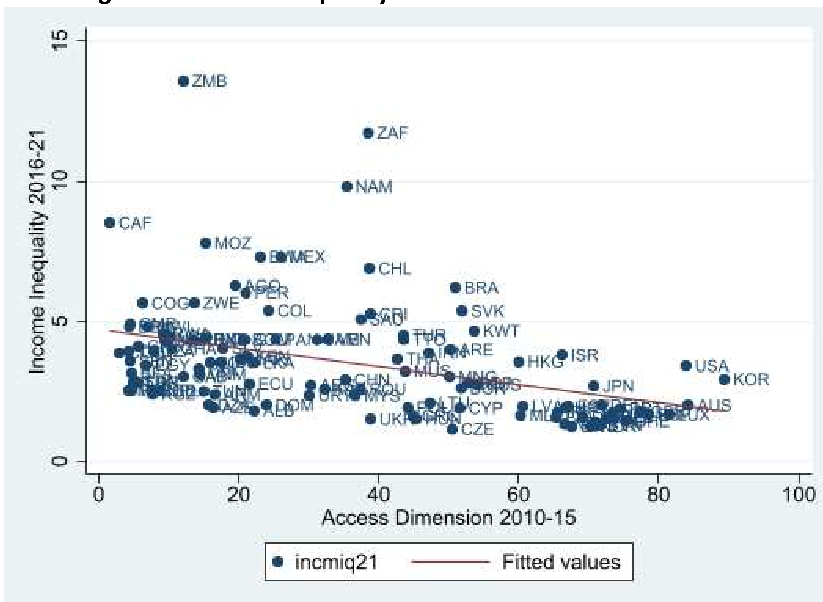
Sarma, Mandira. (2012). Index of financial inclusion — A measure of financial sector inclusiveness. Competence Centre on Money, Trade, Finance and Development 1207, Hochschule fūr Technik und Wirtschaft, Berlin.

Turegano, David Martinez and Alicia Garcia Herrero. (2018). Financial inclusion, rather than size, is the key to tackling income inequality. *Singapore Economic Review*, 63(1): 167-184. World Scientific.

Zellner, Arnold. (1986). On assessing prior distributions and bayesian regression analysis with g-prior distributions. In P. Goel and A. Zellner (eds.). Bayesian Inference and Decision Techniques: Essays in Honor of Bruno de Finetti (389-399). Amsterdam: North-Holland/Elsevier.

Figures and Tables

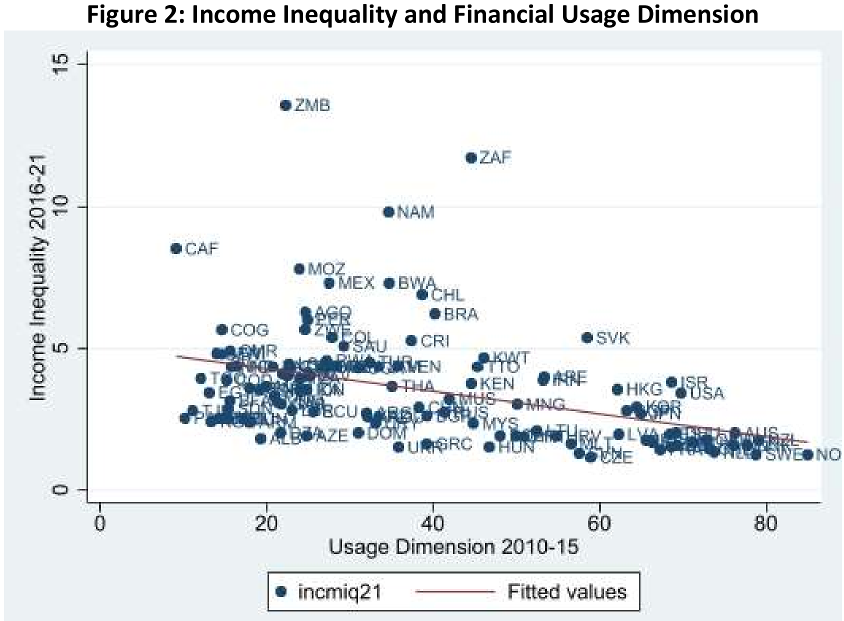
Figure 1: Income Inequality and Financial Access Dimension



Notes: Income inequality measure refers to the ratio between Top 10% and Bottom 50% income shares based on World Inequality Database, average from 2016-2021. Access dimension refers to the unweighted average of indicators on financial account, debit and credit card ownership, commercial bank branches, number of ATMS, and account for wages, whenever data is available from 2010-2015. Sample excludes Italy which is an outlier.

Source: Authors' calculations.

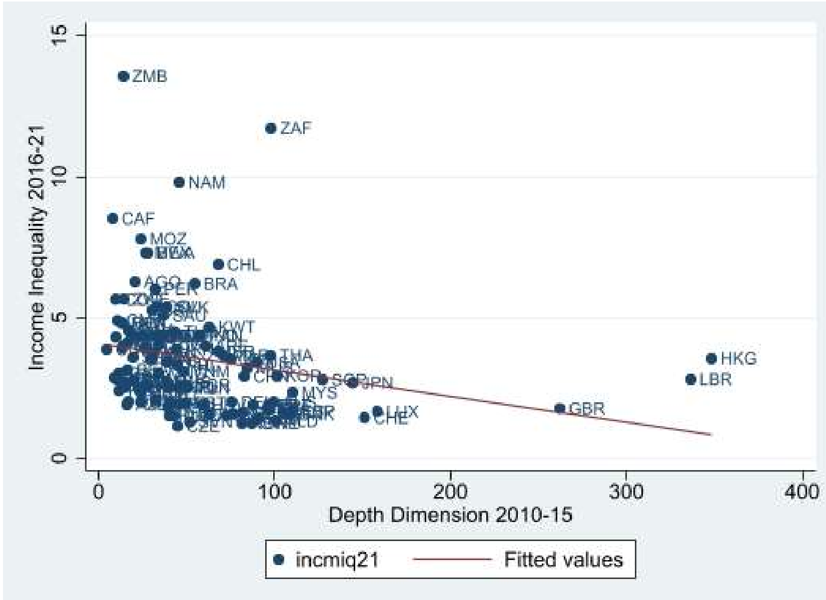
Figure 2: Income Inequality and Financial Usage Dimension



Notes: Income inequality measure refers to the ratio between Top 10% and Bottom 50% income shares based on World Inequality Database, average from 2016-2021. Usage dimension refers to the unweighted average of indicators on withdrawals, digital payments, savings, account to receive wages, and borrowing whenever data is available from 2010-2015. Sample excludes Italy which is an outlier.

Source: Authors' calculations.

Figure 3: Income Inequality and Financial Depth Dimension



Notes: Income inequality measure refers to the ratio between Top 10% and Bottom 50% income shares based on World Inequality Database, average from 2016-2021. Financial depth dimension refers to the unweighted average of indicators on domestic credit, private sector credit, financial system deposits, bank assets, insurance company assets, bank deposits, and stock market capitalisation whenever data is available from 2010-2015. Sample excludes Italy which is an outlier.
Source: Authors' calculations.

Table 1: Descriptive Statistics

Variables	High-Income Countries					Low-Income Countries				
	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max
Income Inequality	72	3.48	3.23	1.14	24.59	44	4.12	2.00	1.49	13.57
Education completion	72	36.05	15.64	5.36	75.00	44	18.95	15.33	1.40	73.65
Labour force ratio	72	41.69	12.67	5.36	68.43	44	45.36	14.58	13.57	75.12
Median age	72	33.10	7.67	5.36	45.00	44	20.60	5.20	13.57	38.70
Trade openness	72	99.49	74.09	5.36	419.20	44	68.37	32.61	13.57	157.00
Financial Access	72	49.32	20.62	12.07	89.37	44	12.79	10.62	1.56	50.13
Financial institution account	72	70.74	25.79	17.37	100.00	44	26.82	18.74	3.30	84.77
Owns a credit card	72	29.07	20.19	2.89	77.91	44	3.46	4.44	0.42	23.42
Owns a debit card	72	54.94	26.23	6.80	98.63	44	14.11	14.09	1.00	66.70
Owns a debit or credit card	72	59.75	26.27	8.89	98.90	44	15.02	14.48	1.38	68.24
Commercial bank branches	72	24.04	16.19	3.25	82.61	44	9.17	11.26	0.73	66.76
Automated teller machines	72	73.85	46.04	10.94	280.06	44	13.98	16.39	0.78	89.99
Account used to receive wages	72	32.86	17.06	7.20	66.68	44	6.97	6.02	1.42	30.05
Financial Usage	72	48.82	18.37	18.03	84.96	44	21.46	9.56	9.14	53.27
Made a withdrawal	72	81.21	12.79	48.01	98.60	44	60.67	12.64	35.96	84.76
Made or received a digital payment	72	65.26	25.76	12.27	99.69	44	24.65	17.75	6.99	86.73
Received wages in a financial account	72	32.91	17.02	7.20	66.68	44	7.61	6.07	1.42	30.05
Saved at a financial institution	72	30.84	19.29	1.23	78.41	44	11.30	7.05	0.92	29.48
Borrowed from a formal financial institution	72	22.85	11.57	4.67	62.54	44	9.18	7.07	0.91	34.23
Received digital payments	72	51.73	23.86	8.97	92.86	44	17.73	15.15	2.79	74.86
Made a digital payment	72	56.93	28.59	7.23	98.12	44	19.05	15.67	2.94	71.61
Financial Depth	72	69.89	53.57	11.30	348.41	44	32.97	49.23	4.65	336.48
Domestic credit to private sector	72	82.56	50.55	12.19	246.68	44	30.15	20.67	4.97	91.06
Domestic credit to private sector by banks	72	76.88	47.23	12.16	246.56	44	28.30	18.13	4.94	82.30
Financial system deposits	72	84.40	123.62	16.90	1000.00	44	50.19	113.85	8.56	778.32
Deposit money banks assets	72	87.54	48.29	16.24	247.40	44	55.05	113.94	5.52	776.94
Insurance company assets	72	26.00	30.93	0.87	121.40	44	3.80	4.44	0.02	18.27
Bank deposits	72	72.43	58.46	16.90	355.73	44	50.10	113.64	8.56	776.94
Stock market capitalisation	72	59.44	132.04	0.00	1072.69	44	13.20	20.72	0.00	80.56

Notes: Refer to Appendix 1 for list of countries included in the sample. See Appendix 2 for variable definition and sources.
Source: Authors' calculations.

Table 2. Baseline Results for Bayesian Model Averaging
(Low-income countries, all financial inclusion indicators)

	(1)			(2)		
Candidate Regressors	**PIP**	**Posterian Mean**	**Posterior SD**	**PIP**	**Posterian Mean**	**Posterior SD**
Account used to receive wages	**0.70**	0.3268	0.3182	**0.68**	0.3023	0.3097
Automated teller machines	**0.85**	0.0587	0.0418	**0.84**	0.0555	0.0408
Bank deposits to GDP	0.25	-0.0010	0.1248	0.24	0.0000	0.1166
Borrowed from a formal financial institution	0.43	-0.0384	0.0615	0.43	-0.0358	0.0591
Commercial bank branches	**0.97**	-0.0743	0.0355	**0.97**	-0.0705	0.0348
Deposit money banks assets to GDP	0.27	0.0030	0.0098	0.25	0.0027	0.0092
Domestic credit to private sector	0.55	0.0486	0.0666	0.54	0.0450	0.0638
Domestic credit to private sector by banks	0.44	-0.0425	0.0692	0.43	-0.0392	0.0661
Education completion	0.34	-0.0068	0.0139	0.33	-0.0064	0.0134
Financial institution account	0.07	-0.0014	0.0121	0.07	-0.0014	0.0121
Financial system deposits to GDP	0.25	-0.0033	0.1261	0.24	-0.0038	0.1180
Insurance company assets to GDP	0.08	-0.0025	0.0208	0.08	-0.0023	0.0204
Labour force ratio	**0.74**	-0.0202	0.0186	**0.75**	-0.0194	0.0182
Made a digital payment	0.58	-0.0570	0.0843	0.57	-0.0530	0.0799
Made a withdrawal	**1.00**	-0.0629	0.0218	**1.00**	-0.0595	0.0215
Made or received a digital payment	0.27	0.0245	0.1107	0.26	0.0214	0.1042
Median age	**1.00**	-0.4137	0.0926	**1.00**	-0.3921	0.0913
Owns a credit card	0.07	0.0026	0.0308	0.08	0.0028	0.0312
Owns a debit card	0.55	0.0650	0.1002	0.55	0.0620	0.0983
Owns a debit or credit card	0.47	0.0505	0.0996	0.47	0.0482	0.0976
Received digital payments	0.39	-0.0409	0.0731	0.39	-0.0389	0.0702
Received wages in a financial institution account	**0.82**	-0.3565	0.2888	**0.81**	-0.3296	0.2817
Saved at a financial institution	**1.00**	0.1528	0.0558	**1.00**	0.1450	0.0550
Stock market capitalisation	0.11	-0.0010	0.0055	0.11	-0.0009	0.0053
Trade openness	0.13	0.0008	0.0035	0.14	0.0008	0.0034

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. Refer to Appendix 1 for list of countries included in the sample. In columns (1) the prior for the parameter is a local empirical Bayes estimate of *g*, while in column (2), *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.
Source: Authors' estimates.

Table 3. Baseline Results for Bayesian Model Averaging

(High-income countries, all financial inclusion indicators)

	(1)			(2)		
Candidate Regressors	**PIP**	**Posterian Mean**	**Posterior SD**	**PIP**	**Posterian Mean**	**Posterior SD**
Account used to receive wages	0.22	-0.0194	0.2278	0.20	-0.0172	0.2099
Automated teller machines	0.15	0.0010	0.0042	0.16	0.0011	0.0042
Bank deposits to GDP	0.09	0.0001	0.0029	0.09	0.0001	0.0028
Borrowed from a formal financial institution	0.25	-0.0122	0.0318	0.25	-0.0114	0.0306
Commercial bank branches	0.33	0.0082	0.0171	0.32	0.0075	0.0163
Deposit money banks assets to GDP	0.50	0.0074	0.0106	0.47	0.0065	0.0100
Domestic credit to private sector	0.27	0.0051	0.0123	0.25	0.0045	0.0114
Domestic credit to private sector by banks	0.29	-0.0065	0.0145	0.26	-0.0055	0.0134
Education completion	0.11	0.0020	0.0102	0.11	0.0017	0.0095
Financial institution account	0.13	0.0035	0.0159	0.13	0.0032	0.0152
Financial system deposits to GDP	0.07	-0.0001	0.0008	0.07	-0.0001	0.0008
Insurance company assets to GDP	0.12	0.0012	0.0057	0.11	0.0011	0.0054
Labour force ratio	0.14	-0.0032	0.0129	0.14	-0.0030	0.0125
Made a digital payment	0.21	0.0069	0.0244	0.21	0.0064	0.0231
Made a withdrawal	0.06	-0.0006	0.0091	0.07	-0.0007	0.0092
Made or received a digital payment	0.60	0.0474	0.0570	0.57	0.0427	0.0545
Median age	**1.00**	-0.2020	0.0547	**1.00**	-0.1921	0.0533
Owns a credit card	0.09	0.0003	0.0129	0.10	0.0005	0.0126
Owns a debit card	0.06	-0.0002	0.0066	0.06	-0.0001	0.0062
Owns a debit or credit card	0.07	0.0003	0.0108	0.08	0.0003	0.0109
Received digital payments	0.33	-0.0236	0.0476	0.31	-0.0215	0.0451
Received wages in a financial institution account	0.21	-0.0047	0.2282	0.21	-0.0044	0.2102
Saved at a financial institution	0.54	-0.0255	0.0339	0.51	-0.0229	0.0322
Stock market capitalisation	0.33	0.0013	0.0027	0.31	0.0012	0.0025
Trade openness	0.46	-0.0032	0.0050	0.42	-0.0028	0.0047

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. Refer to Appendix 1 for list of countries included in the sample. In columns (1) the prior for the parameter is a local empirical Bayes estimate of *g*, while in column (2), *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.
Source: Authors' estimates.

Table 4. Baseline Results for Bayesian Model Averaging
(Low-income countries, financial inclusion dimensions)

	(1)			(2)		
Candidate Regressors	**PIP**	**Posterian Mean**	**Posterior SD**	**PIP**	**Posterian Mean**	**Posterior SD**
Education completion	0.35	-0.0036	0.0116	0.37	-0.0038	0.0118
Financial access indicators	**0.73**	0.0649	0.0757	**0.68**	0.0620	0.0711
Financial depth indicators	0.35	-0.0010	0.0032	0.37	-0.0011	0.0032
Financial usage indicators	0.55	-0.0327	0.0604	0.51	-0.0305	0.0578
Labour force ratio	0.49	-0.0067	0.0140	0.43	-0.0068	0.0138
Median age	**0.86**	-0.1940	0.1094	**0.95**	-0.1930	0.0891
Trade openness	0.32	-0.0002	0.0042	0.32	-0.0002	0.0044

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. Financial access, financial depth, and financial usage were computed as unweighted averages of indicators belonging to each dimension. Refer to Appendix 1 for list of countries included in the sample. In columns (1) the prior for the parameter is a local empirical Bayes estimate of *g*, while in column (2), *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.
Source: Authors' estimates.

Table 5. Baseline Results from Bayesian Model Averaging
(High-income countries, financial inclusion dimensions)

	(1)			(2)		
Candidate Regressors	**PIP**	**Posterian Mean**	**Posterior SD**	**PIP**	**Posterian Mean**	**Posterior SD**
Education completion	0.27	0.0000	0.0125	0.28	-0.0001	0.0123
Financial access indicators	0.46	0.0223	0.0384	0.46	0.0205	0.0364
Financial depth indicators	0.38	0.0029	0.0061	0.38	0.0027	0.0058
Financial usage indicators	0.38	-0.0144	0.0361	0.37	-0.0132	0.0342
Labour force ratio	0.40	-0.0114	0.0220	0.39	-0.0107	0.0212
Median age	**0.99**	-0.2011	0.0599	**0.99**	-0.1896	0.0593
Trade openness	0.35	-0.0015	0.0037	0.35	-0.0015	0.0036

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. Financial access, financial depth, and financial usage were computed as unweighted averages of indicators belonging to each dimension. Refer to Appendix 1 for list of countries included in the sample. In columns (1) the prior for the parameter is a local empirical Bayes estimate of *g*, while in column (2), *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.
Source: Authors' estimates.

Appendix 1: Country Income Groups

Table A1: Country Sample and Income Groups

High Income Countries		Low Income Countries
Albania	Mexico	Algeria
Argentina	Namibia	Angola
Armenia	Netherlands	Bangladesh
Australia	New Zealand	Benin
Austria	Norway	Bolivia
Azerbaijan	Panama	Burkina Faso
Belgium	Paraguay	Cameroon
Botswana	Peru	Central African Republic
Brazil	Poland	Congo, Dem. Rep.
Bulgaria	Portugal	Congo, Rep.
Chile	Romania	Cote d'Ivoire
China	Russian Federation	Egypt, Arab Rep.
Colombia	Saudi Arabia	El Salvador
Costa Rica	Singapore	Ghana
Croatia	Slovak Republic	Honduras
Cyprus	Slovenia	India
Czech Republic	South Africa	Indonesia
Denmark	Spain	Iran, Islamic Rep.
Dominican Republic	Sweden	Kenya
Ecuador	Switzerland	Kyrgyz Republic
Estonia	Thailand	Lesotho
Finland	Trinidad and Tobago	Liberia
France	Turkiye	Malawi
Gabon	United Arab Emirates	Mali
Germany	United Kingdom	Mongolia
Greece	United States	Morocco
Guatemala	Uruguay	Mozambique
Hong Kong SAR, China	Venezuela, RB	Nepal
Hungary		Nicaragua
Ireland		Pakistan
Israel		Philippines
Italy		Rwanda
Jamaica		Senegal
Japan		Sri Lanka
Jordan		Sudan
Kazakhstan		Tajikistan
Korea, Rep.		Tanzania
Kuwait		Togo
Latvia		Tunisia
Lithuania		Uganda
Luxembourg		Ukraine
Malaysia		Vietnam
Malta		Zambia
Mauritius		Zimbabwe

Notes: High-income group includes countries that are classified by World Bank as high-income and upper middle-income countries, while low-income group are those that are classified as lower middle-income and low-income countries.
Source: Authors classification.

Appendix 2: Variables, Notes, and Sources

Table A2: Data Notes and Sources

Variable (Code)	Notes	Sources
Income Inequality (incmiq)	Ratio between Top 10% and Bottom 50% income shares	World Inequality Database
Education completion (educ)	Secondary school completion of those between age 25 to 64 (%)	Barro-Lee Dataset; and national sources
Labour force (lbrfrc)	Labour force participation rate for ages 15-24, total (%)	World Development Indicators, World Bank
Median age (mdage)	Median age (in years)	United Nations Population Division
Trade openness (trade)	Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product (%)	World Development Indicators, World Bank
Financial access (d1a21)	Unweighted average of financial access indicators	Authors' calculations
Financial institution account (finacct)	The percentage of respondents (age 15+) who report having an account (by themselves or together with someone else) at a bank or another type of financial institution.	Financial Inclusion Database, World Bank
Owns a credit card (ccrdt)	The percentage of respondents (age 15+) who report having a credit card.	Financial Inclusion Database, World Bank
Owns a debit card (cdbt)	The percentage of respondents (age 15+) who report having a debit card.	Financial Inclusion Database, World Bank
Owns a debit or credit card (cdcrd)	The percentage of respondents (age 15+) who report having a credit or debit card.	Financial Inclusion Database, World Bank
Commercial bank branches (brnch)	Commercial bank branches per 100,000 adults	World Development Indicators, World Bank; and national sources
Automated teller machines (atm)	Automated teller machines per 100,000 adults	World Development Indicators, World Bank; and national sources
Account used to receive wages (actwg	The percentage of respondents (age 15+) who report using their accounts at a formal financial institution to receive money or payments for work or from selling goods in the past 12 months.	Financial Inclusion Database, World Bank
Financial usage (d2a21)	Unweighted average of financial usage indicators	Authors' calculations
Made a withdrawal (wthdrw)	Among respondents (age 15+) with a financial institution account, the percentage who report withdrawing money from their account one or more times in the past year.	Financial Inclusion Database, World Bank

Variable (Code)	Notes	Sources
Made or received digital payment (mrdgt)	The percentage of respondents (age 15+) who report using mobile money, a debit or credit card, or a mobile phone to make a payment from an account--or report using the internet to pay bills or to buy something online or in a store--in the past year.	Financial Inclusion Database, World Bank
Saved at a financial institution (saved)	The percentage of respondents (age 15+) who report saving or setting aside any money at a bank or another type of financial institution in the past year.	Financial Inclusion Database, World Bank
Received wages in a financial institution account (rcdwgf)	The percentage of respondents (age 15+) who report receiving any money from an employer in the past year in the form of a salary or wages for doing work, and who received it directly into a financial institution account, into a card, or through a mobile phone.	Financial Inclusion Database, World Bank
Borrowed from a formal financial institution (brwff)	The percentage of respondents (age 15+) who report borrowing any money from a bank or another type of financial institution or using a credit card in the past year.	Financial Inclusion Database, World Bank
Received digital payments (rcvdpy)	The percentage of respondents (age 15+) who report using a mobile money account, a debit or credit card, or a mobile phone to receive a payment into an account in the past year.	Financial Inclusion Database, World Bank
Made a digital payment (mkdpy)	The percentage of respondents (age 15+) who report using mobile money, a debit or credit card, or a mobile phone to make a payment from an account; or who report using the internet to pay bills or to buy something online or in a store in the past year.	Financial Inclusion Database, World Bank
Financial depth (d3a21)	Unweighted average of financial depth indicators	Authors' calculations
Domestic credit to private sector (dcps)	Domestic credit to private sector (% of GDP) refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment.	World Development Indicators, World Bank; and national sources
Domestic credit to private sector by banks (dcpsb)	Domestic credit to private sector by banks (% of GDP) refers to financial resources provided to the private sector by other depository corporations (deposit taking corporations except central banks), such as through loans, purchases of nonequity	World Development Indicators, World Bank; and national sources

Variable (Code)	Notes	Sources
	securities, and trade credits and other accounts receivable, that establish a claim for repayment.	
Financial system deposits (fnsys)	Demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP.	Global Financial Development Database, World Bank; and national sources
Deposit money banks assets (dmby)	Total assets held by deposit money banks as a share of GDP.	Global Financial Development Database, World Bank; and national sources
Insurance company assets (insray)	Ratio of assets of insurance companies to GDP.	Global Financial Development Database, World Bank; and national sources
Bank deposits (bndpy)	The total value of demand, time and saving deposits at domestic deposit money banks as a share of GDP. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits.	Global Financial Development Database, World Bank; and national sources
Stock market capitalisation (stkcpy)	Total value of all listed shares in a stock market as a percentage of GDP.	Global Financial Development Database, World Bank; and national sources

Appendix 3: Sensitivity Test Results

Table A3: Sensitivity Test Results from Bayesian Model Averaging

(All countries and all indicators)

	(1)			(2)		
Candidate Regressors	**PIP**	**Posterian Mean**	**Posterior SD**	**PIP**	**Posterian Mean**	**Posterior SD**
Account used to receive wages	0.23	0.0504	0.1662	0.22	0.0463	0.1583
Automated teller machines	0.34	0.0032	0.0062	0.35	0.0033	0.0062
Bank deposits	0.23	-0.0010	0.0028	0.22	-0.0009	0.0027
Borrowed from a formal financial institution	0.16	-0.0054	0.0186	0.16	-0.0052	0.0182
Commercial bank branches	0.22	0.0042	0.0115	0.20	0.0038	0.0109
Deposit money banks assets	0.11	0.0001	0.0022	0.10	0.0001	0.0021
Domestic credit to private sector	0.45	0.0096	0.0150	0.44	0.0089	0.0144
Domestic credit to private sector by banks	0.32	-0.0071	0.0141	0.31	-0.0065	0.0135
Education completion	0.08	0.0008	0.0053	0.08	0.0008	0.0052
Financial institution account	0.23	0.0075	0.0189	0.23	0.0073	0.0185
Financial system deposits	0.13	-0.0002	0.0009	0.13	-0.0002	0.0009
Insurance company assets	0.16	0.0018	0.0063	0.16	0.0017	0.0061
Labour force ratio	0.40	-0.0092	0.0156	0.40	-0.0089	0.0152
Made a digital payment	0.24	-0.0111	0.0303	0.23	-0.0107	0.0294
Made a withdrawal	0.04	0.0001	0.0044	0.05	0.0001	0.0046
Made or received a digital payment	**0.91**	0.1073	0.0637	**0.90**	0.1027	0.0633
Median age	**1.00**	-0.1932	0.0436	**1.00**	-0.1879	0.0429
Owns a credit card	0.05	0.0000	0.0058	0.06	0.0001	0.0058
Owns a debit card	0.05	0.0003	0.0059	0.06	0.0003	0.0058
Owns a debit or credit card	0.12	0.0030	0.0132	0.12	0.0029	0.0129
Received digital payments	**0.91**	-0.0958	0.0555	**0.90**	-0.0916	0.0554
Received wages in a financial institution account	0.18	-0.0418	0.1648	0.17	-0.0384	0.1571
Saved at a financial institution	0.44	-0.0177	0.0271	0.43	-0.0168	0.0264
Stock market capitalisation	0.41	0.0015	0.0025	0.40	0.0014	0.0024
Trade openness	0.44	-0.0028	0.0043	0.42	-0.0026	0.0041

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. In column (1) the prior for the parameter is a local empirical Bayes estimate of g, while in column (2), a in the mean of the Beta distribution is set equal to 3 to determine g. In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.

Source: Authors' estimates.

Table A4: Sensitivity Test Results from Bayesian Model Averaging

(All countries and by dimensions using simple average)

Candidate Regressors	PIP (1)	Posterian Mean (1)	Posterior SD (1)	PIP (2)	Posterian Mean (2)	Posterior SD (2)
Education completion	0.25	0.0013	0.0085	0.25	0.0012	0.0084
Financial access indicators, simple average	**0.94**	0.0789	0.0450	**0.93**	0.0754	0.0445
Financial depth indicators, simple average	0.24	0.0002	0.0024	0.24	0.0002	0.0024
Financial usage indicators, simple average	**0.68**	-0.0460	0.0463	**0.66**	-0.0435	0.0454
Labour force ratio	0.48	-0.0125	0.0179	0.48	-0.0121	0.0175
Median age	**1.00**	-0.2251	0.0501	**1.00**	-0.2176	0.0501
Trade openness	0.27	-0.0006	0.0023	0.27	-0.0006	0.0023

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. In column (1) the prior for the parameter is a local empirical Bayes estimate of *g*, while in column (2), *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.

Source: Authors' estimates.

Table A5: Sensitivity Test Results from Bayesian Model Averaging

(Low-income countries, by dimensions using principal component analysis)

Candidate Regressors	PIP (1)	Posterian Mean (1)	Posterior SD (1)	PIP (2)	Posterian Mean (2)	Posterior SD (2)
Education completion	0.31	-0.0033	0.0112	0.36	-0.0036	0.0115
Financial access indicators, pca	**0.78**	0.0763	0.0835	**0.72**	0.0760	0.0783
Financial depth indicators, pca	0.34	-0.0008	0.0028	0.36	-0.0009	0.0030
Financial usage indicators, pca	0.64	-0.0419	0.0655	0.56	-0.0407	0.0633
Labour force ratio	0.41	-0.0063	0.0136	0.42	-0.0067	0.0137
Median age	**0.84**	-0.1992	0.1195	**0.96**	-0.2070	0.0924
Trade openness	0.29	-0.0001	0.0040	0.32	-0.0002	0.0043

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. In column (1) the prior for the parameter is a local empirical Bayes estimate of *g*, while in column (2), *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.

Source: Authors' estimates.

Table A6: Sensitivity Test Results from Bayesian Model Averaging

(High-income countries, by dimensions using principal component analysis)

Candidate Regressors	PIP (1)	Posterian Mean (1)	Posterior SD (1)	PIP (2)	Posterian Mean (2)	Posterior SD (2)
Education completion	0.27	-0.0003	0.0125	0.28	-0.0003	0.0123
Financial access indicators, pca	0.42	0.0202	0.0411	0.41	0.0186	0.0389
Financial depth indicators, pca	0.37	0.0029	0.0062	0.37	0.0027	0.0060
Financial usage indicators, pca	0.36	-0.0139	0.0389	0.36	-0.0128	0.0369
Labour force ratio	0.40	-0.0119	0.0224	0.40	-0.0111	0.0214
Median age	**0.99**	-0.1984	0.0591	**0.99**	-0.1865	0.0586
Trade openness	0.35	-0.0015	0.0036	0.35	-0.0014	0.0035

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. In column (1) the prior for the parameter is a local empirical Bayes estimate of *g*, while in column (2), *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. In both columns, a uniform model prior is chosen, and a birth-death sampler is used to evaluate the model space.

Source: Authors' estimates.

Table A7: Sensitivity Test Results from Bayesian Model Averaging

(Low-income countries)

Candidate Regressors	(1) PIP	(2) PIP	(3) PIP	(4) PIP	(5) PIP	(6) PIP	(7) PIP	(8) PIP
Account used to receive wages	**0.67**	**0.67**	**0.66**	**0.70**	**0.67**	**0.68**	**0.67**	**0.67**
Automated teller machines	**0.84**	**0.84**	**0.66**	**0.85**	**0.67**	**0.84**	**0.84**	**0.84**
Bank deposits	0.26	0.26	0.62	0.27	0.63	0.27	0.27	0.26
Borrowed from a formal financial institution	0.45	0.45	0.62	0.47	0.63	0.46	0.45	0.45
Commercial bank branches	**0.96**	**0.96**	**0.66**	**0.96**	**0.66**	**0.96**	**0.96**	**0.96**
Deposit money banks assets	0.28	0.28	0.64	0.30	**0.65**	0.29	0.28	0.28
Domestic credit to private sector	0.53	0.53	**0.66**	0.56	**0.67**	0.54	0.53	0.54
Domestic credit to private sector by banks	0.43	0.43	**0.65**	0.45	**0.67**	0.44	0.43	0.43
Education completion	0.33	0.33	0.63	0.34	**0.65**	0.33	0.33	0.33
Financial institution account	0.10	0.10	0.64	0.10	0.63	0.11	0.10	0.10
Financial system deposits	0.27	0.26	0.63	0.28	0.63	0.27	0.26	0.27
Insurance company assets	0.10	0.10	0.61	0.11	0.62	0.10	0.10	0.10
Labour force ratio	**0.73**	**0.73**	**0.66**	**0.73**	**0.66**	**0.73**	**0.73**	**0.73**
Made a digital payment	0.56	0.56	0.64	0.58	**0.65**	0.57	0.56	0.56
Made a withdrawal	**1.00**	**1.00**	**0.70**	**1.00**	**0.70**	**1.00**	**1.00**	**1.00**
Made or received a digital payment	0.30	0.29	0.64	0.31	**0.65**	0.30	0.30	0.30
Median age	**1.00**	**1.00**	**0.83**	**1.00**	**0.90**	**1.00**	**1.00**	**1.00**
Owns a credit card	0.10	0.10	0.64	0.10	0.64	0.11	0.11	0.11
Owns a debit card	0.54	0.55	**0.66**	0.55	**0.65**	0.54	0.55	0.55
Owns a debit or credit card	0.48	0.48	**0.67**	0.48	**0.65**	0.49	0.48	0.48
Received digital payments	0.41	0.40	0.64	0.40	**0.65**	0.41	0.41	0.41
Received wages in financial institution account	**0.80**	**0.80**	**0.68**	**0.83**	**0.69**	**0.81**	**0.80**	**0.80**
Saved at a financial institution	**1.00**	**1.00**	**0.69**	**1.00**	**0.68**	**1.00**	**1.00**	**1.00**
Stock market capitalisation	0.12	0.13	0.61	0.13	0.62	0.13	0.13	0.13
Trade openness	0.14	0.14	0.61	0.15	0.62	0.15	0.14	0.14

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. In column (1), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to $2+2/K^2$ to determine *g*. The model prior is uniform, and a birth-death sampler is used to evaluate the model space. *K* is the number of regressors. In column (2), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to $2+2/N$ to determine *g*. The model prior is uniform, and a birth-death sampler is used to evaluate the model space. *N* is the number of regressors. In column (3), the prior for the parameter is a local empirical Bayes estimate of *g*. The model prior is random, and a birth-death sampler is used to evaluate the model space. In column (4), the prior for the parameter is a local empirical Bayes estimate of *g*. The model prior is uniform, and a reversible-jump sampler is used to evaluate the model space. In column (5), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. The model prior is random, and a birth-death sampler is used to evaluate the model space. In column (6), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. The model prior is uniform, and a reversible-jump sampler is used to evaluate the model space. In column (7), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to $2+2/K^2$ to determine *g*. The model prior is uniform reversible-jump sampler is used to evaluate the model space. In column (8), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to $2+2/N$ to determine *g*. The model prior is uniform, and a reversible-jump sampler is used to evaluate the model space.

Source: Authors' estimates.

Table A8: Robustness Test Results from Bayesian Model Averaging

(Low-income countries, by dimensions using simple average)

Candidate Regressors	(1) PIP	(2) PIP	(3) PIP	(4) PIP	(5) PIP	(6) PIP	(7) PIP	(8) PIP
Education completion	0.32	0.32	0.46	0.32	0.48	0.37	0.32	0.32
Financial access indicators, simple average	**0.66**	**0.66**	**0.68**	**0.72**	**0.68**	**0.68**	**0.66**	**0.66**
Financial depth indicators, simple average	0.33	0.33	0.47	0.32	0.47	0.37	0.33	0.33
Financial usage indicators, simple average	0.48	0.48	0.61	0.54	0.57	0.51	0.48	0.48
Labour force ratio	0.39	0.39	0.53	0.46	0.51	0.43	0.39	0.39
Median age	**0.95**	**0.96**	**0.89**	**0.84**	**0.93**	**0.95**	**0.95**	**0.96**
Trade openness	0.28	0.28	0.43	0.34	0.44	0.32	0.28	0.28

Notes: PIP refers to the posterior inclusion probabilities. PIPs equal to greater than 0.65 are in boldface. SD is standard deviation. In column (1), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to $2+2/K^2$ to determine *g*. The model prior is uniform, and a birth-death sampler is used to evaluate the model space. *K* is the number of regressors. In column (2), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to $2+2/N$ to determine *g*. The model prior is uniform, and a birth-death sampler is used to evaluate the model space. *N* is the number of regressors. In column (3), the prior for the parameter is a local empirical Bayes estimate of *g*. The model prior is random, and a birth-death sampler is used to evaluate the model space. In column (4), the prior for the parameter is a local empirical Bayes estimate of *g*. The model prior is uniform, and a reversible-jump sampler is used to evaluate the model space. In column (5), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. The model prior is random, and a birth-death sampler is used to evaluate the model space. In column (6), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to 3 to determine *g*. The model prior is uniform, and a reversible-jump sampler is used to evaluate the model space. In column (7), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to $2+2/K^2$ to determine *g*. The model prior is uniform reversible-jump sampler is used to evaluate the model space. In column (8), the prior for the parameter is where *a* in the mean of the Beta distribution is set equal to $2+2/N$ to determine *g*. The model prior is uniform, and a reversible-jump sampler is used to evaluate the model space.

Source: Authors' estimates.