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What Really Drives Financial Inclusion? Evidence from a Meta-Analysis of 3,817 Estimates

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Abstract:
We present a comprehensive meta-analysis of the determinants of financial inclusion, synthesizing 3,817 estimates from 102 studies published between 2013 and 2024. To reconcile divergent findings, we convert all results to a common unbiased metric—the partial correlation coefficient corrected via the UWLS+3 approach—and apply recent advances in meta-analysis methodology. The evidence shows that while reported effects are small and positive, they are systematically inflated by publication bias; once corrected, the underlying impact is more modest but remains economically meaningful. Among determinants, income-related factors play only a minor role, whereas technology, infrastructure, and persistence over time have far greater influence. Regional variation is substantial: Sub-Saharan Africa and MENA benefit more consistently from inclusion drivers than Europe or Asia. The results temper overly optimistic interpretations of individual studies and provide robust benchmarks for policymakers seeking to design effective and realistic strategies for advancing inclusive finance worldwide.

JEL: C83, G21, O16
Keywords: Financial inclusion, banks, meta-analysis, model uncertainty, publication bias, Bayesian model averaging

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1. Introduction

Financial inclusion has emerged as a pivotal area of research in the field of development economics due to its essential role for sustainable economic growth. Early empirical studies by Burgess and Pande (2005), Beck et al. (2007), Demirgüç-Kunt and Klapper (2013) highlight that improved access to financial services can reduce poverty, improve household welfare, and support small business activity. Subsequently, recent contributions by Park and Mercado (2015), Allen et al. (2016), Demirgüç-Kunt and Singer (2017), Ozili (2018), Galdo (2025) has further linked inclusive financial systems to broader goals of income equality, formal economic participation, increased labor participation and decision-making power, and resilience against economic shocks. These outcomes are particularly emphasized in the context of developing economies where exclusion from financial services remains widespread. In response, empirical research on the determinants of financial inclusion has expanded rapidly over the past two decades and identified numerous potential determinants ranging from individual-level factors such as income, education, and gender to institutional factors, including banking infrastructure, regulatory frameworks, and technological innovation. However, the increasing opacity in the growing empirical evidence does not provide guidance on the key determinants that facilitate or hinder financial inclusion across contexts. Even now, in the 21st century, we still do not know the general effect size of those determinants. Hence, following the standard guidelines in the field (Havránek *et al.*, 2020), we provide the first quantitative synthesis and meta-analysis of the financial inclusion literature, covering over a decade of global research, and delivering some conclusive evidence on the determinants of financial inclusion.

Figures 1 and 2 provide an illustrative background motivating the key research questions for our analysis. One hundred and six studies have attempted to estimate the determinants in question, and collectively they have produced 3,817 estimates. Meta-analysis allows us to assess the combined effect sizes from these individual studies of different subgroups to address the inconsistencies in findings and also to explore why studies produce different results (Geyer-Klingeberg et al., 2020). By using the novel weighted average ($UWLS_{+3}$) approach of Stanley et al. (2024), we recompute these estimates into a comparable unbiased metric and observe that the results differ greatly both across as well as within studies. First, Figure 1 highlights a decline in the median reported effect size in studies over time, accompanied by a marked reduction in variance. The viewpoint is that recent studies tend to report slightly smaller median effects, which may highlight a decline in the impact of financial inclusion determinants compared to older

studies.[1] However, this declining trend may also reflect a shift or advancement in methodologies and the use of larger and more representative data, rather than diminishing real-world impact. Earlier studies, constrained by limited data availability and nascent analytical tools, tended to produce more dispersed and, in some cases, inflated estimates. As the field matured, richer datasets and more rigorous estimation strategies have resulted in more conservative, precise estimates.

Second, Figure 2 presents the distribution of reported effect sizes in the surveyed literature. Two features stand out: (i) the distribution is positively skewed, with a high concentration of large positive effects and a scarcity of large negative ones, and (ii) the modal value lies just above zero, indicating that many estimates cluster around small but positive effects. These patterns could point to publication bias, which we discuss in the next sections. Nevertheless, they may also reflect systematic heterogeneity across primary studies.

Several methodological and contextual factors may explain the observed heterogeneity in results. First, the measurement of financial inclusion itself varies considerably across studies, ranging from simple binary indicators of account ownership (Demirgüç-Kunt and Klapper, 2013; Allen *et al.*, 2016) to complex multidimensional index measures that incorporate access, usage, and quality dimensions (Sarma, 2008; Sarma and Pais, 2011; Cámara and Tuesta, 2014) to the exclusion of certain social groups and individuals from accessing the financial system (Leyshon and Thrift, 1995; Sharma and Changkakati, 2022). Chakravartyl and Pal (2010) propose an axiomatic approach to measuring financial inclusion. The approach improves upon Sarma (2008) by allowing the index to be utilized to determine the percentage contribution (Gupte, Venkataramani and Gupta, 2012). These measurement differences can substantially affect estimated relationships. Based on the measures employed, we hypothesize that some effects may vary depending on whether binary or continuous inclusion measures are used.

Second, the choice of explanatory variables and empirical specifications differs substantially, with some studies focusing on individual-level determinants (Allen *et al.*, 2016; Wale and Makina, 2017; Antonio and Magante, 2023; Ocharive and Iworiso, 2024) while others emphasize macro-institutional factors (Le *et al.*, 2019; Nsiah and Tweneboah, 2023). Third, data sources, sample compositions, and estimation techniques vary widely, potentially introducing systematic biases that affect the comparability of results across studies. Cross-country analyses using Global Findex data (for instance, Allen et al., 2016) provide a broad global coverage, but

[1] Earlier studies (mid-2000s to early 2010s) report a mix of positive and negative effects, with some large positive outliers (above 0.4) and a few extreme negative outliers (below -1.5). In more recent years (post-2018), the reported effect sizes cluster more tightly around zero, suggesting a potential convergence in estimates or more conservative effect reporting.

they may mask important country-specific heterogeneity. Conversely, single-country studies (see Coulibaly, 2022; Nayak et al., 2024) offer deeper institutional insights but potentially limited external validity. While most research relies on cross-sectional correlations (Allen *et al.*, 2016; Zins and Weill, 2016), a growing number of studies employ quasi-experimental methods (instrumental variables, difference-in-difference) to establish causal relationships. However, such quasi-experimental studies remain relatively rare and often focus on specific interventions rather than broader determinants.

Determinants of financial inclusion broadly cover the following categories: macroeconomic, demographic, education and human capital, banking structure, socioeconomic, technology and infrastructure, and institutional factors. Macroeconomic factors typically include variables such inflation, interest rate, employment rate, and gross domestic product (GDP), while demographic determinants often encompass age, gender, and residence status (Zins and Weill, 2016). Institutional factors, such as regulatory frameworks and the presence of financial institutions, also play a critical role in shaping the landscape of financial inclusion (Nsiah and Tweneboah, 2023). Furthermore, the rapid advancement of technology has introduced new avenues for financial access, particularly through mobile banking and digital financial services, which help bridge the gaps left by traditional banking systems (Shen, Hueng and Hu, 2020). For instance, high-speed internet access has been shown to stimulate foreign direct investment in the financial sector (Mensah and Traore, 2024), facilitate remittances, and contribute to broader structural transformations (Dappe and Lebrand, 2024).

Given the considerable heterogeneity in the approach, context and findings across studies, we shed light on two key questions: what are the most consistent determinants of financial inclusion across empirical studies? Can we explain why different studies come to such different conclusions? The use of meta-analysis is essential here because it provides rigorous quantitative methods that precisely identify and disentangle the key factors driving variation in estimated effects (Havranek, Horvath and Zeynalov, 2016). While meta-analysis methods have been applied within economics in numerous fields, such as financial economics (De Batz and Kočenda, 2024; Yang *et al.*, 2024; Bortnikova, Bajzik and Kočenda, 2025), energy and environmental economics (Havranek, Irsova and Janda, 2012; Havranek and Kokes, 2015), international economics (Tokunaga and Iwasaki, 2017), and macroeconomics (Ehrenbergerova, Bajzik and Havranek, 2023; Iwasaki and Kočenda, 2024), there has been no meta-analysis examining the determinants of financial inclusion.

Our main contribution is threefold. First, we present the first meta-analysis of the economics literature on the determinants of financial inclusion. We standardize the different estimates reported in studies using the partial correlation coefficients (PCC) adjusted via the novel unrestricted weighted least squares average ($UWLS_{+3}$) method designed by Stanley et al. (2024) to yield an unbiased common metric. The biases associated with standard PCCs (Olkin and Pratt, 1958; Stanley and Doucouliagos, 2023) have been successfully addressed with an adjustment to the PCCs degrees of freedom via the $UWLS_{+3}$ method of Stanley et al. (2024). To the best of our knowledge, we present one of the first large meta-analyses that apply $UWLS_{+3}$ to integrate the impact of several thousand estimates via an unbiased common metric. Second, using methods that address model uncertainty, we trace the differences in results to differences in estimation context. Due to the large number of potential explanatory variables and the uncertainty regarding which factors most systematically explain cross-study variation, we employ Bayesian Model Averaging (BMA) techniques. BMA addresses model uncertainty by running numerous regressions with different combinations of explanatory variables and computing weighted averages based on model fit and parsimony (Steel, 2020). We account for potential collinearity using the dilution prior (Kroupova, Havranek and Irsova, 2024), which gives less weight to models with a small determinant of the correlation matrix. Doing so allows us to gauge the effect of omitted variables, measurement error, and other identification issues. We performed a frequentist check for the variables with the highest posterior inclusion probability. Further, we employ frequency model averaging, as proposed by Wang et al. (2009) and subsequently employed by Ehrenbergerova et al. (2023), as a robustness check.

Third, we use recently developed techniques to correct for the effect of publication bias potentially existing in related literature. In addressing publication bias, we employ the Funnel Asymmetry Test & Precision Effect Test (FAT-PET), the Weighted Average of Adequately Powered (Ioannidis, Stanley and Doucouliagos, 2017), p-uniform (van Aert and van Assen, 2021), kinked meta-regression model (Bom and Rachinger, 2019), Stem-based method (Furukawa, 2019), Selection model (Andrews and Kasy, 2019), and the Funnel plot (Stanley and Doucouliagos, 2010) for the graphical analysis of publication bias. Furthermore, we test for selective reporting in the literature using the p-hacking test (Elliott et al., 2022).

Growing evidence from high-quality meta-analyses confirms the widespread nature of publication bias across various economic fields (Stanley, 2005; Gerber, 2008; Moreno *et al.*, 2009; Andrews and Kasy, 2019; Bajzik *et al.*, 2020; Elliott, Kudrin and Wüthrich, 2022). Publication bias describes a situation in which researchers favour studies with significant positive effects, as

they are perceived as more policy-relevant than null results. The problem is that unusual results, like positive or no effects, are easy to notice, but big negative results, which could also be flawed due to data or methods, are harder to spot (Kroupova, Havranek and Irsova, 2024). This creates a bias because researchers tend to focus more on certain types of results. Such bias is not only common but also difficult to eliminate entirely, which is why it is important for researchers to identify and correct for the bias (Kroupova, Havranek and Irsova, 2024).

Our analysis highlights several key findings. First, the mean reported effect without any adjustment is 0.044. Second, we identify significant publication bias in the financial inclusion literature, with studies systematically favouring positive effects over null or negative results. The funnel plot analysis reveals asymmetric distribution of estimates, with a concentration of small positive effects among less precise studies and notable underrepresentation of negative effects. Formal statistical tests confirm this bias, with OLS estimation yielding a publication bias coefficient of 0.642. After correcting for publication bias using various techniques (WAAP, Kinked, p-uniform, stem-based, selection model), the true underlying effect ranges between 0.024 and 0.051. This result is substantially smaller than the uncorrected mean effect. However, our results showed no evidence of p-hacking. Further, our Bayesian Model Averaging analysis reveals substantial heterogeneity in reported effects across different methodological approaches and study characteristics. It is worth noting that the measurement of financial inclusion significantly influences results. Studies employing an index constructed through principal component analysis (PCA) report more negative effect sizes compared to other dimensional measures.

The rest of the paper is organised as follows: Section 2 details the data collection procedure, data transformation, and independent variables, and provides a brief descriptive analysis of the data. Section 3 presents the results of the publication bias. Section 4 presents the results of our meta-regression analysis (MRA) of literature heterogeneity. Finally, Section 5 concludes the paper with a summary and recommendations for policy implications.

2. Data

In this section, we describe the data collection process for the meta-analysis. The meta-analysis is based on a systematic review and coding of empirical studies that investigate the determinants of financial inclusion. We restrict our attention to studies that employ quantitative methods and provide effect size estimates derived from either micro-level or macro-level data. Put simply, we collect estimates from models that can be reduced to the following regression:

$$Financial\ inclusion_{it} = \beta_0 + \beta_1 determinants_{it} + \varepsilon_{it}, \quad (1)$$

where *Financial inclusion*$_{it}$, denotes financial inclusion levels for country *i* in time *t*, *determinants*$_{it}$ denotes the set of micro and macro variables employed as determinants, and ε_{it} is the error term. Our main variable of interest is β_1, which we collect from studies, together with their standard error and other variables that help us to explain heterogeneity and the context in which the coefficient was achieved. For our estimations and analysis, we standardise all estimates to a comparable metric, the partial correlation coefficient (PCC), using the UWLS$_{+3}$ transformation. The corrected unbiased PCC is computed in the following way:

$$\text{PCC} = \frac{t}{\sqrt{t^2 + df_{+3}}} \quad (2)$$

Where $t = \frac{\beta_1}{s_{\beta 1}}$ is the conventional *t*-test for the statistical significance of X_1 in the explanation of *Y*, and *df = n – j – 1,* is the degree of freedom available to the multiple regression, eq. (1). It is well established that individual PCCs are biased downward (Olkin and Pratt, 1958), while meta-analyses of PCC are, in contrast, biased upward (Stanley and Doucouliagos, 2023).[2] Hence, we follow the recent correction proposed by Stanley et al. (2024), which reduces such bias to scientific triviality. Specifically, we mitigate the biases associated with standalone PCCs by employing UWLS$_{+3}$ of Stanley et al. (2024) and compute the unbiased versions of the PCC. As shown in equation (2), a simple adjustment to the degrees of freedom resolves the issue: we increase the degrees of freedom by three to effectively eliminate the small-sample bias in PCCs and obtain an unbiased common metric.

When used with a corrected variance formula (S_2^2), UWLS$_{+3}$ yields more accurate and reliable PCCs, maintains robustness under selection for statistical significance, and accounts for additive heterogeneity without relying on the restrictive assumptions of fixed-effects models. The use of UWLS$_{+3}$ in the meta-analysis of PCCs helps reduce bias and errors better than traditional random-effects models and is more robust when studies vary in size or only report significant results. UWLS$_{+3}$ tends to give results that are closer to the true effect and are less sensitive to issues like publication bias or heterogeneity in smaller studies. Finally, the UWLS$_{+3}$ exhibits better statistical properties, especially in the presence of publication selection bias or when between-study heterogeneity is correlated with sample size or the standard error of the effect estimates.

[2] The variance estimates of PCCs, especially those derived from small samples, are susceptible to notable upward bias, leading to distorted meta-analytic results (Stanley et al., 2024).

In line with the literature, we focus on the three dimensions of financial inclusion: access, usage, and quality (Sharma and Changkakati, 2022). Each of these dimensions captures different aspects of how individuals and businesses engage with financial services. When put together, these dimensions provide a comprehensive view of financial inclusion. In a comprehensive view, financial inclusion is highlighted through the adoption of an index, the Financial Inclusion Index (FII) (Cámara and Tuesta, 2014; Park and Mercado, 2015; Nguyen, 2021).

Access dimension refers to the availability of financial services to individuals and businesses (Beck, Demirgüç-Kunt and Levine, 2007; Honohan, 2008). Key measures under this dimension include the ownership of bank accounts, the number of bank branches per 100,000km, the number of automated teller machines (ATMs) in a region, and the presence of mobile banking services. While access is necessary, it is not sufficient for financial inclusion. The usage dimension assesses how actively individuals and businesses utilize financial services once they have access (Chakravartyl and Pal, 2010; Amidžić, Massara and Mialou, 2014). Financial usage may include total loan amount, savings, borrowings, bank deposits, credit cards, and debit cards. The quality dimension is also used to describe financial products or services that aim to improve the financial service experience, fulfil financial needs, and ease financial burdens. Measures under this dimension may include the volume of life insurance, non-life insurance, interest cost on loans, emergency source of funds, government payments, and digital payments. As mentioned earlier, the financial inclusion index (FII) aggregates the various dimensions of financial inclusion into a single metric. Many studies have employed the use of the FII in their studies (Amidžić, Massara and Mialou, 2014; Park and Mercado, 2015; Demirgüç-Kunt and Singer, 2017; Sharma and Changkakati, 2022). However, several studies commonly employ the concept of Sarma (2008), which uses arbitrary dimensional weights (1, 0.5, and 0.5 for access, availability, and usage, respectively) or the use of statistical weights through the Principal Component Analysis (PCA) (Cámara and Tuesta, 2014).

We search for studies reporting on the effects of the determinants of financial inclusion, following the approach and guidelines of (Havránek *et al.*, 2020). We compiled a list of primary studies using Google Scholar. Google Scholar serves as an extensive search engine with access to full-text studies. Google's algorithm searches the title, abstract, keywords, and full text of studies, thereby increasing our coverage of relevant published estimates, regardless of the specific wording in titles, abstracts, or keywords. We identified our primary studies using different combinations of search references. We use the search query “" financial inclusion" ("determinants" OR "factors" OR "drivers") ("regression" OR "empirical" OR "econometric") ("account ownership" OR "mobile

money" OR "digital finance" OR "financial access" OR "financial inclusion index")". See Appendix Figure B1 for details. We examined the abstracts and results of the first 800 studies returned by our search to determine the presence of relevant estimates. Further, we apply the snowballing approach to inspect the reference list of the 30 most cited papers per our search results to augment the list of literature. We restricted our review to studies in the English language and terminated the search in December 2024.

We included in our dataset only studies that concurrently satisfied two key conditions. First, we only considered studies that report some measures of statistical precision, such as standard errors, t-statistics, or p-values. These measures are essential for implementing meta-analysis techniques and for addressing publication bias. Specifically, each study must report either the standard error directly or provide sufficient information to reconstruct it, as standard errors are used both as weights and as explanatory variables in our meta-regression models of publication bias. Second, we require studies to report clear and detailed information on their characteristics and relevant control variables. Following Stanley (2001), we do not exclude studies based on publication type. Our dataset, therefore, includes not only peer-reviewed journal articles but also working papers, book chapters, and theses or dissertations. To maintain the integrity of our sample, we carefully cross-checked all entries to eliminate duplicates. Differences in study quality are accounted for in the subsequent stages of analysis.

Our dataset comprises 102 studies, yielding a total of 3,817 effect sizes related to various determinants of financial inclusion. Appendix Table A1 and Appendix C provide full details on the studies included in the meta-analysis. These studies cover both developed and developing countries, capturing the diverse experiences and contexts of financial inclusion globally. We categorize the determinants identified in the literature into several broad groups: macroeconomic indicators, demographic characteristics, credit and financial depth measures, income-related variables, education and human capital indicators, banking structure, technological infrastructure, and institutional quality. In addition, we include the lag of the dependent variable as a determinant to account for studies that examine the persistence of financial inclusion over time. Each variable is systematically coded to reflect its relationship with financial inclusion and to enable us to systematically analyze the direction and magnitude of effects. We also document the methodological features of each study, including sample size, data sources, regional or country focus, econometric techniques applied, and publication quality.

The earliest study included in the meta-analysis was published in 2013 (Chithra and Selvam, 2013), while the most recent is by Eshun and Kočenda (2025), available online in

December 2024. Based on the Google Scholar citation counts as of April 2025, the most cited studies in our sample are Allen et al. (2016) with 2,124 citations, followed by Zins and Weill (2016) with 962 citations and Fungáčová and Weill (2015) having 755 citations.

Figure 3 presents a box plot of the effect size estimates arranged chronologically by year of publication. The figure reveals a clear cluster of high dispersion linked to earlier studies. While most studies report estimates near the overall mean effect of financial inclusion (0.044), many report significantly higher values, and negative estimates also appear with some frequency. Overall, the figure highlights substantial heterogeneity across studies, a decline in estimate dispersion over time, and a growing volume of studies with converging results in recent years. Appendix Table A2 summarizes the variation in determinants, organized into their main categories, which we further examine through meta-regression analysis. Additionally, Appendix Figure B2 provides a visual overview of the heterogeneity in the literature, which we thoroughly discuss in Section 4.

The results suggest that how financial inclusion is measured significantly influences the estimated effects. Specifically, studies using quality dimensions and composite financial inclusion index report higher weighted mean elasticities of 0.096 and 0.083, respectively, compared to those focusing on access (0.077) or usage dimensions (0.056). Among the determinant categories, the lagged dependent variable, which captures the persistence of financial inclusion over time, exhibits the strongest effect, with a weighted mean of 0.454. Technology and infrastructure variables follow suit with a substantial mean impact of 0.171. In contrast, income-level factors are associated with the weakest effect, yielding a mean elasticity of just 0.023. The choice of estimation technique also plays a critical role in shaping the reported outcomes. Ordinary Least Squares (OLS) produces the highest average effect size (0.156), followed by probit models (0.036), then fixed effects estimations (0.008). Several other methods, such as Pooled OLS, Feasible Generalized Least Squares (FGLS), and Panel-Corrected Standard Errors (PCSE), are grouped under a general category labeled "Other methods," which collectively yield a weighted mean effect of 0.120. Regional variation is also apparent. Studies focusing on the Middle East and North Africa report higher elasticities (0.187), whereas those based in Europe report more modest effects (0.013). In terms of data structure, time series studies yield the highest elasticities (0.184), while cross-sectional analyses report the lowest (0.057).

3. Publication Bias

Publication bias is a common issue present in empirical research and accounted for in meta-analysis. The bias arises when studies with significant or "positive" results are more likely to be published than those with non-significant or "negative" findings. As a result, the published research may not reflect the full range of evidence, leading to an inflated perception of the true effect being studied (Bortnikova, Havránek and Irsova, 2024). In some cases, this phenomenon is referred to as misreporting bias (Cullen, 2023). According to Bruns et al. (2019), researchers often draw attention to significant results by reporting standard errors and using asterisks (or similar markers) to denote statistical significance. However, these visual cues do not always match the actual test statistics (such as the t-values), which may indicate signs of bias in the reporting. Bortnikova et al. (2025) explain that publication bias tends to arise for two main reasons. First, researchers tend to avoid publishing findings that contradict established expectations. Second, researchers may be influenced by what McCloskey and Ziliak (2019) termed the Lombard effect. Borrowed from how people raise their voices in noisy environments to be heard, this effect captures how researchers "shout" about small p-values to draw attention to their results in a competitive academic setting. In doing so, they may neglect the real-world relevance of these findings. This kind of selective reporting has become more common in several areas of economics and finance and has been documented in recent studies (Valickova, Havranek and Horvath, 2015; Tokunaga and Iwasaki, 2017; Iwasaki and Ono, 2024; De Batz and Kočenda, 2024; Iwasaki and Kočenda, 2024; Malovaná *et al.*, 2025).

In addition to publication bias, p-hacking represents another form of selective reporting in meta-analysis (Bruns and Ioannidis, 2016). Unlike publication bias, which is about what gets published, p-hacking is about how the results are obtained in the first place. Researchers may tweak their models or methods until they get significant results that are more likely to be accepted for publication. In practice, the line between p-hacking and publication bias can be blurry, and the two often go hand in hand. However, in this paper, we use the term publication bias in its more general meaning, separating it from p-hacking only when necessary.

Detecting potential publication bias is one of the most important analytical steps. A widely used, albeit informal, method for identifying such bias is the visual inspection of a funnel plot (Stanley and Doucouliagos, 2010). The use of a funnel plot displays a study's precision on the vertical axis, typically measured as the inverse of the standard error (1/SE), against the estimated effect size on the horizontal axis (Stanley and Doucouliagos, 2010). The effect size could be measured as elasticity, a regression coefficient, or a partial correlation coefficient.

In the absence of publication bias or other forms of selection, regardless of the measure of precision one uses, the distribution of estimates should appear symmetrical and shaped like an inverted funnel around the true effect size. Smaller studies, which are generally less precise, are plotted lower on the graph and tend to show more variability in their estimates, creating a wider spread at the bottom of the funnel. Larger, more precise studies cluster towards the top (Egger *et al.*, 1997). A symmetrical funnel shape indicates that study estimates are distributed randomly around the true effect, regardless of their statistical significance. In contrast, asymmetry in the funnel plot, especially the absence of small, non-significant estimates, can be a strong visual signal of publication bias or small-study effects. Thus, symmetry in the funnel plot serves as a key diagnostic criterion for assessing the presence or absence of publication selection. Figure 4 presents a funnel plot visualizing the precision of the estimated effect of the determinants of financial inclusion.

The funnel plot presented in Figure 4 shows asymmetry in the distribution of estimated effects. There is a concentration of studies reporting small positive effects of financial inclusion determinants, with estimates clustering between 0 and 0.1 on the horizontal axis. We show that this clustering is obvious among studies with lower precision (toward the base of the funnel), where the inverse of standard errors approaches zero. At the same time, there is a noticeable underrepresentation of estimates reporting negative or null effects, particularly on the left side of the funnel, which contributes to the overall asymmetry. The skewed concentration of positive effects, particularly among less precise studies, suggests that researchers may engage in specification searching or selective reporting to achieve statistically significant results that favour positive relationships between various determinants and financial inclusion outcomes.[3] Such a pattern is consistent with the presence of publication bias as documented in meta-analytical literature (Egger *et al.*, 1997; Bortnikova, Havránek and Irsova, 2024). According to Egger, "positive" findings are often published multiple times, increasing their chances of being identified and included in meta-analyses.

We complement the graphical evidence of publication bias by applying formal statistical tests that quantify both its presence and magnitude. These tests provide an objective assessment of whether smaller studies, typically associated with larger standard errors, tend to report systematically different effect sizes than larger, more precise studies. In particular, we examine

[3] "It is the peculiar and perpetual error of the human understanding to be more moved and excited by affirmatives than negatives, whereas it ought duly and regularly to be impartial (Bacon, 1878)"

this relationship by regressing the reported effect sizes (standardized using UWLS+3-corrected PCCs) on their corresponding standard errors, following the approach introduced by Card and Krueger (1995). As noted by Zigraiova and Havranek (2016), a statistically significant relationship between effect sizes and their standard errors is indicative of publication selection. If studies reporting negative or statistically insignificant results are systematically excluded from the published literature, this selection process results in a positive correlation between effect sizes and their standard errors due to heteroskedasticity in the regression model (Stanley, 2008; Zigraiova and Havranek, 2016). To formally test this, we estimate the following equation:

$$PCC_i = \beta_0 + \beta_1 SE(PCC_i) + u_i \quad (3)$$

Table 1 presents the results based on the full sample of 3,817 estimates. Panel A, Column 1 reports the baseline tests. The OLS regression results indicate a positive estimate of publication bias at 0.642, which is statistically significant at the 5% level. After correcting for this bias, the adjusted effect size decreases to 0.021 and remains statistically significant, suggesting a small but positive overall impact of the determinants of financial inclusion. We further address potential endogeneity of the standard errors by implementing the recent novel meta-analysis instrumental variable estimator (MAIVE) designed by Irsova et al., (2025). MAIVE uses the inverse of the square root of the sample size as an instrument to reduce spurious precision and produce reliable bias correction than the simple mean. The MAIVE estimator shows a higher publication bias coefficient of 1.129, significant at the 1% level. The finding indicates that endogeneity may have led to an underestimation of bias in the OLS model. However, the bias-corrected effect under the MAIVE treatment drops to 0.005 and is not statistically significant. The finding suggests that, once endogeneity is properly accounted for, the underlying effect of the determinants may be negligible.

Panel B reports the results from alternative estimation techniques. The Between Effects (BE) model yields a publication bias estimate of 1.102, indicating that studies reporting larger effect sizes are more likely to appear in the literature. The pattern suggests the presence of selective reporting, where findings that highlight stronger relationships between financial inclusion determinants and outcomes are overrepresented in the literature. After correcting for this bias, the adjusted effect size falls to 0.0243, implying that the true underlying effect is considerably smaller once selection bias is accounted for.

In contrast, the Fixed Effects (FE) estimation shows no evidence of publication bias. However, FE models can be problematic in meta-analyses because some studies contribute disproportionately large numbers of estimates, often due to robustness checks, while others

provide only a few (Bortnikova, Havránek and Irsova, 2024). Despite this limitation, the FE model yields a bias-corrected effect size of 0.113, which is notably larger than the BE estimate. We show that after controlling for within-study variation, the estimated relationship between financial inclusion determinants and outcomes becomes more pronounced. The Random Effects model, which incorporates both within- and between-study variation, presents a slightly negative but statistically insignificant bias coefficient. Nevertheless, the bias-corrected effect size is 0.108 and statistically significant at the 1% level. These results imply that when accounting for all sources of heterogeneity, publication bias may obscure rather than exaggerate the true effect.

Panel C presents results from several nonlinear publication bias correction methods, designed to address the limitations of the linear meta-regression model (MRM). Unlike linear approaches, these techniques do not assume a constant relationship between effect sizes and their standard errors. Instead, they are based on the premise that low-precision estimates, those with large standard errors, are more susceptible to publication bias, particularly near conventional thresholds of statistical significance (e.g., $t \approx 1.96$). In contrast, highly precise estimates (e.g., $t > 10$) are presumed to be less influenced by selective reporting. We report results for five techniques: the weighted average of adequately powered (WAAP) (Ioannidis, Stanley and Doucouliagos, 2017), the kinked model (Bom and Rachinger, 2019), the p-uniform (Van Aert and Van Assen, 2021), the Stem-based method (Furukawa, 2019), and the Selection model (Andrews and Kasy, 2019).

The WAAP estimator restricts the analysis to studies with statistical power above 80%, following the approach outlined by Ioannidis, Stanley and Doucouliagos (2017) and implemented in recent work by Kroupova et al. (2024). The rationale is that publication bias is more likely to affect marginally significant results than highly significant ones. Applying the WAAP estimator in Column 1 of Table C yields a corrected mean effect of 0.024 ($p < 0.001$), suggesting that, even when only well-powered studies are considered, the positive relationship between financial inclusion determinants and outcomes remains statistically significant and robust.

The Endogenous Kink (EK) model by (Bom and Rachinger, 2019) takes a different approach by estimating a data-driven "kink point" that separates high-precision (presumably unbiased) estimates from those more likely to be affected by publication bias. While the EK model shares conceptual similarities with WAAP, both distinguish between more and less precise estimates. They differ in two key respects. First, WAAP relies on power calculations, whereas EK uses statistical significance to define the cutoff. Second, WAAP excludes imprecise estimates from analysis, whereas EK retains them but corrects for potential bias among more significant estimates.

Applying the EK method produces a corrected effect size of 0.026, closely aligning with the WAAP estimate and reinforcing the conclusion that the observed effects are not driven solely by publication bias but are likely due to genuine underlying relationships.

We further employed the p-uniform method (Van Aert and Van Assen, 2021) to correct for publication bias by utilizing only statistically significant effect sizes, based on the assumption that under the true effect, p-values should follow a uniform distribution. When applied to our data, the p-uniform method yields a corrected effect size of 0.033, which is slightly larger than the WAAP and EK estimates. Our finding further supports the presence of a genuine positive relationship between financial inclusion determinants and outcomes, even after adjusting for potential publication selection.

When we apply the stem-based method of Furukawa (2019) to assess publication bias, the bias-adjusted average effect size (0.014) is substantially smaller than unadjusted estimates. We introduce the selection model (Andrews and Kasy, 2019) to estimate the likelihood that negative and insignificant elasticities will be reported and then re-weight the reported estimates using the computed probabilities. The selection model reveals a statistically significant average true effect of 0.051 after correcting for publication bias.

We test for p-hacking among reported estimates by applying the Cox-Shi p-hacking tests (Elliott et al., 2022) over the p-value range of [0.00, 0.15]. Our results show no evidence of p-hacking. The test for monotonicity and theoretical bounds showed a p-value of 0.608, while the conditional chi-squared histogram test yielded a p-value of 0.463. These high p-values suggest that the distribution of reported p-values in our meta-analytic dataset is consistent with expectations under the null hypothesis and shows no signs of suspicious bunching around conventional significance thresholds.

The results of the nonlinear techniques are broadly consistent with the linear meta-regression approaches but suggest an even smaller corrected mean effect size. In all cases, the bias-corrected estimates are substantially smaller than the simple reported mean: estimates range from 0.014 (Furukawa, 2019) to 0.051 (Andrews and Kasy, 2019). The median estimate for the nonlinear techniques is 0.026, indicating that the true underlying relationship between financial inclusion determinants and outcomes is considerably weaker than what appears in the published literature. Together with the linear approaches, the results suggest that 0.025 is a reasonable estimate for the mean effect of financial inclusion determinants. We conclude that publication bias in the literature is substantial and it likely exaggerates the mean reported effects of financial inclusion determinants.

4. Heterogeneity

In this section, we explore why the reported estimates in the financial inclusion literature vary so widely. Specifically, we extend model (2) by including characteristics of the studies and their estimates, allowing us to examine the factors driving this heterogeneity. In meta-analysis, statistical heterogeneity refers to the variation in effect sizes across studies that cannot be explained by sampling error alone. Understanding the sources of this variation is essential for drawing meaningful conclusions from a body of empirical evidence (Higgins et al., 2003). In our case, the considerable differences in estimated effects suggest that more than just random variation is at play. Heterogeneity can arise from multiple factors, including differences in sample populations, data type, study designs, and empirical methodologies (Bajzik et al., 2020). We examine these issues systematically and construct a dataset containing 38 study-level characteristics, including study design features and standard errors. We then employ Bayesian Model Averaging (BMA) to explore how these variables influence the reported effect sizes while accounting for model uncertainty. For ease of exposition, the variables are divided into seven groups: measurement of financial inclusion, types of financial inclusion determinants, estimation technique, country/region, data structure variation, and publication-related characteristics. We present a correlation matrix in Appendix Figure B2 to show that there are only minimal correlations between the variables. The corresponding variables are defined and summarized in Table 2.

4.1. Details of variables explaining heterogeneity

4.1.1. Measurement of Financial Inclusion

Researchers use various specifications to capture and measure financial inclusion. As discussed earlier in Section 2, the concept has matured, and researchers have moved from using simple, one-off indicators to more comprehensive, multidimensional measures that reflect the complexity of financial systems. Broadly, we observe three types of measurement approaches. The first is single-variable measures, where studies rely on one indicator, like the number of ATMs, the number of bank accounts, or credit-to-GDP ratios, to capture financial inclusion (Zins and Weill, 2016; Antonio and Magante, 2023). The second approach is dimensional measures, which combine several indicators within specific categories such as access, usage, or quality (Cámara and Tuesta, 2014). For example, the use of both bank deposits and the credit-to-deposit ratio to capture usage. Finally, composite index measures bring together multiple indicators across dimensions to produce a single summary score, often using statistical methods like principal component analysis. According to Cámara and Tuesta (2014), the concept of financial inclusion goes beyond single

indicators such as the number of deposit accounts, ATMs, or bank branches, loans, and debit cards, and therefore, necessitates a comprehensive measurement approach that captures the multidimensionality of financial inclusion. Hence, several studies in our meta-analysis adopt composite index approaches. Nsiah and Tweneboah (2023) develop a comprehensive financial inclusion index that incorporates indicators across access, usage, and barrier dimensions. Similarly, Bekele (2023), Nayak et al. (2024), and Nasreen et al. (2025) employ multidimensional indexes that synthesize various aspects of financial inclusion into single measures. Some studies use less conventional measures, such as domestic credit to the private sector (Nagpal, Jain and Jain, 2019) or the Global Financial Services Utilization Rate (Senou, Ouattara and Acclassato Houensou, 2019). These measures fall outside the typical access-usage-quality framework, and we categorize them as other measures.

We generate a set of dummy variables to capture the type of financial inclusion measure used in each study. These include binary indicators equal to one if the study employs a financial access measure, a financial usage measure, a financial quality measure, or a composite financial inclusion index. Studies that use other types of measures serve as the reference category in our analysis.

Regarding the composite financial inclusion index, its construction can vary significantly (Sarma, 2008; Cámara and Tuesta, 2014). For example, Sarma (2008) and (Gebregziabher Gebrehiwot and Makina, 2019) construct an index using arbitrarily assigned dimensional weights. In contrast, the more commonly adopted method is Principal Component Analysis (PCA), which applies statistical rather than arbitrary weights to derive the index.

4.1.2. Type of financial inclusion determinant

The primary studies often differ in terms of the type of determinants employed in estimation. Most studies on financial inclusion focus on income levels, education, and demographic factors. Income-related variables are used in 29% of the estimates, making them the most used, followed closely by education and human capital (23%) and demographic factors (21%). Further, macroeconomic factors appear in just 17% of studies, while institutional (2%), technology & infrastructure (2%), bank structure (3%), and credit/financial depth variables (3%) are rarely used. The lag of the dependent variable, which captures dynamic effects, is included in only 1% of studies. As shown by (Demirgüç-Kunt and Singer, 2017), and Urueña-Mejia and Perez (2022), the choice of determinant category significantly affects estimated outcomes. For the same type of

macroeconomic determinant, per capita income tends to exhibit a stronger contribution to financial inclusion levels than other macroeconomic indicators (Urueña-Mejia and Perez, 2022).

4.1.3. Estimation Characteristics

We further control for five estimation techniques commonly used in financial inclusion research: ordinary least squares (OLS), fixed effects, logit, probit, and generalized method of moments (GMM). The last category, classified as other methods, is used as the reference category. As to the frequency of use, OLS is employed in 6% of studies, representing the most frequent approach despite potential endogeneity concerns. Fixed effects estimation appears in 4% of studies and typically produces more conservative estimates by controlling for time-invariant country characteristics. Logit and probit models are used in 16% and 50% of studies, respectively, reflecting the binary nature of many financial inclusion indicators such as account ownership. GMM techniques appear in 12% of studies, primarily addressing endogeneity through instrumental variable approaches or dynamic panel specifications. GMM estimation often yields different coefficient magnitudes compared to OLS, as it accounts for simultaneity between financial inclusion and its determinants (Gebregziabher Gebrehiwot and Makina, 2019). Other estimation methods, including random effects and Tobit models, comprise 16% of the sample and serve as our reference category.

Empirical literature demonstrates that estimation method choice significantly influences reported effects in financial inclusion research. For instance, OLS estimates can be biased due to unobserved heterogeneity and omitted variable bias, often leading to inflated coefficient estimates. Fixed effects models mitigate this by controlling for group-specific or individual-specific effects, resulting in more conservative (smaller) and reliable estimates when such heterogeneity is present (Nygård and Thoresen, 2025). However, fixed effects estimators can also introduce bias in the estimates if there is dynamic misspecification or omitted within-group variation correlated with regressors (Plümper and Troeger, 2019). Hence, GMM typically results in smaller (weaker) estimated relationships compared to OLS or FE, as GMM corrects for the upward bias that endogeneity introduces in OLS estimates (Lu and Wooldridge, 2020).

4.1.4. Regional Coverage

The geographical distribution of studies in our meta-analysis reveals significant regional variations that may contribute to heterogeneity in financial inclusion findings. We categorize countries into six regional groups: Asia, Europe, Latin America & Caribbean, Middle East & North Africa, and Sub-Saharan Africa. Studies that cover or fall within more than one of these primary regions are

coded under the category for multi-country/region. In the meta-regression, we use multi-country/region as the reference category. Following the World Bank development classification system, we distinguish the countries between developed and developing economies. We classify studies that cover both developed & developing countries as mixed income groups and use this category as the reference group. Sub-Saharan Africa (SSA) accounts for 34% of the studies and is particularly notable for its pioneering role in mobile money innovations and digital financial services. Asia follows with 31% of the studies. The region includes highly banked economies like Singapore (98% of account ownership) and countries with large unbanked populations, such as Cambodia (33%) and Myanmar (48%). Latin America & Caribbean (LAC) represents 5% of studies, while the Middle East & North Africa (MENA) accounts for 1% of the sample. MENA research often focuses on the role of Islamic banking and Sharia-compliant financial products in promoting inclusion (Khmous and Besim, 2020; Ramaian Vasantha, Liew and Kijkasiwat, 2023). European studies remain the least explored, accounting for just 0.15%. European studies tend to emphasize product sophistication and digital adoption rather than basic account access (Eshun and Kočenda, 2025), and also examine different dimensions of financial inclusion when compared to the developing regions. Studies covering multiple countries or regions comprise 28.39% of the sample. Such studies adopt a global, OECD, African, or BRICS perspective. In terms of economic classification, 47.14% of studies focus on developing economies, 19.37% on developed economies, and 33.49% on both.

4.1.5. Dataset structure

We control for the structure and type of dataset, which could be another important source of heterogeneity in the determinants of financial inclusion. Our metadata reveals that approximately 53% of the estimates utilize cross-sectional data, while 41% employ panel data, and 6% rely on time series data. The predominance of cross-sectional studies in financial inclusion research reflects the widespread use of household surveys such as the World Bank's Global Findex Database and national financial inclusion surveys such as Demirgüç-Kunt and Klapper (2013), Fungáčová and Weill (2015), Demirgüç-Kunt (2018), Demirguc-Kunt et al. (2019), and Demirgüç-Kunt et al. (2022). Panel data studies offer significant advantages by allowing researchers to control for time-invariant unobserved characteristics and track changes in financial inclusion status over time. We also control for the number of years covered in each study using a variable for data span. Furthermore, we account for temporal dynamics in reported estimates, particularly the declining

median effect size observed over time (see Figure 1). We do so by including the midpoint year of the underlying dataset as an explanatory variable in our BMA analysis.

In addition, we distinguish between studies using international datasets, such as the World Bank's Global Findex Database, Global Financial Development Database, IMF Financial Access Survey (FAS), and World Development Indicators, and those using national surveys. We expect that studies relying on local surveys may yield different coefficient magnitudes compared to those using international datasets, potentially due to differences in methodology and contextual factors. We further include a financial crisis dummy to control for studies that account for periods of economic stress. Studies spanning crisis periods typically show systematically different relationships between determinants and financial inclusion outcomes (Eshun and Kočenda, 2025).

4.1.6. Publication Characteristics

Publication characteristics serve as an important proxy for the quality of a study and may systematically influence the magnitude of reported effects in financial inclusion research. We account for study quality by including several publication-related variables. First, we introduce a dummy variable indicating whether a study is published in a peer-reviewed journal. Peer review serves as a general filter for research quality and result reliability, even though review standards vary across journals.

We also control for journal quality by accounting for a journal's impact factor, which reflects both citation frequency and editorial selectivity. We address potential concerns regarding journal quality by estimating an alternative BMA model (aside from our baseline estimation) restricted to peer-reviewed studies only. Additionally, the article influence score is incorporated as a further measure of journal standing. Beyond these journal-level indicators, we use Google Scholar citation counts as a study-level proxy for scholarly attention, based on the assumption that more influential or rigorous studies tend to be cited more frequently.[4] Finally, we include the year of publication to account for potential time trends in the literature and methodological improvements over time. Our sample spans from 2013 to 2024, with the highest number of estimates produced in 2019. More studies have been published after 2019 than before, with publications reaching a new plateau covering 2021 (11.22%), 2022 (12.35%), 2023 (12.94%), and 2024 (10.63%).

[4] While citations may be influenced by factors beyond quality, including topic popularity and author networks, they remain a widely used proxy for academic impact (Mammola *et al.*, 2022).

4.2. Estimation

After the exclusion of baseline categories, the set of potential moderators is reduced to 36 explanatory variables. These variables may account for the heterogeneity observed in the reported estimates of financial inclusion determinants. However, their substantial number introduces a classical problem of model uncertainty within our meta-regression framework. Although each variable represents a theoretically grounded source of heterogeneity, the simultaneous inclusion of all variables in a single regression may yield unreliable results due to multicollinearity and overfitting concerns (Raftery, Madigan and Hoeting, 1997). These issues of multicollinearity and overfitting are particularly relevant in meta-analyses, where the number of moderators often approaches or exceeds the number of studies (Stanley and Doucouliagos, 2012).

We address the problem of model uncertainty by employing the Bayesian Model Averaging (BMA) framework following Hoeting et al. (1999). Rather than relying on a single specification, BMA computes coefficient estimates as weighted averages over all possible model combinations. The weighting is based on posterior model probabilities, which are proportional to the product of the integrated likelihood and the prior model probability (Zeugner and Feldkircher, 2015). The BMA method enables robust inference by incorporating model uncertainty into the estimation process (Moral-Benito, 2015). BMA has been applied in recent meta-analyses, including Bajzik et al., (2020); Zigraiova et al. (2021); De Batz and Kočenda (2024); Kroupova et al. (2024); Bajzik et al. (2025).

Each estimated coefficient under BMA corresponds to a posterior mean, calculated as a weighted average across all models in which the variable appears. The associated measure of statistical relevance is the posterior inclusion probability (PIP). PIP is defined as the sum of posterior model probabilities for all models that include the variable. We interpret the PIP as the probability that a variable belongs to the true underlying model explaining variation in financial inclusion estimates (Raftery, 1995). We present the BMA results of our full sample in Figure 5 using a standard model inclusion plot. Variables are ordered by their posterior inclusion probabilities, with the most relevant predictors at the top. The horizontal axis denotes the cumulative posterior model probability, while the colour coding reflects coefficient signs, blue for positive and red for negative effects. When interpreting the strength of evidence, we adopt the approach of Kočenda and Iwasaki (2022) and select moderators whose meta-independent variables have a PIP exceeding a conservative threshold of 0.80; we include them in the meta-regression

analysis (MRA) estimation reported later.[5] In total, twenty (20) variables record PIP values above the conventional 0.8 threshold. The quantitative output of the BMA is reported on the left-hand side of Table 3, which supports the conclusions derived from the graphical representation.

As a robustness check, we check the baseline Bayesian Model Averaging (BMA) results using alternative combinations of g-priors and model priors. Specifically, we compared the Posterior Inclusion Probabilities (PIPs) of all covariates across four prior settings: UIP with uniform model prior, UIP with dilute model prior, BRIC with random model prior, and HQ with random model prior. We present our results in Appendix Figure B3, which shows a high degree of consistency in the ranking of key variables. Hence, our baseline findings are not overly sensitive to prior assumptions. Further, we replicate the BMA estimation using only estimates from peer-reviewed studies. We present our results in Appendix Figure B4 and Table A3. The results from the robustness test are not materially different from our baseline results based on the full dataset of primary studies. These robustness results show that the extent of heterogeneity does not differ significantly between published and unpublished studies.

4.2.1. Measurement of financial inclusion

The BMA results reveal that differences in the methodological choices in measuring financial inclusion substantially influence reported estimates across studies. None of the conventional dimensions, access, usage, or quality, emerges as decisively influential in explaining the heterogeneity of the reported effects. Among them, access-based measures appear to display marginally stronger relevance, albeit with a posterior inclusion probability (PIP) below the conventional significance threshold. The influence of the access dimension might reflect the fact that access-focused measures capture the immediate availability of financial services, which represents the most basic and observable form of financial inclusion progress.

Conversely, studies that employ index measures constructed using principal component analysis (PCA) tend to report more negative effect sizes than other index measures. However, the relevance of the factor specified by the PIP value is below the significance threshold. The statistical averaging effect inherent in composite measures may dilute individual dimension effects. PCA statistically aggregates multiple dimensions of financial inclusion, which may capture broader aspects of financial access, usage, and quality than other index measures. Our findings align with the methodological debates in the financial inclusion literature regarding measurement approaches,

[5] Eicher et al. (2011) argue that moderators with PIP between 0.99 and 1.00 exhibit a decisive impact, between 0.95 and 0.99 a strong impact, and between 0.75 and 0.95 a substantial impact.

where Sarma (2008) advocates arbitrary weights while Cámara and Tuesta (2014) promote PCA to reduce subjectivity bias. Bearing this in mind, it is interesting to note that methodological choice is neutral and does not systematically affect reported relationships.

4.2.2. Financial inclusion determinants

With respect to the determinants of financial inclusion, all examined categories exhibit exceptionally high posterior inclusion probabilities, underscoring their consistent relevance in explaining the variation in reported effects across studies. All categories also produce negative posterior mean estimates, suggesting that studies focusing on these determinants tend to report more cautious or adverse effects on financial inclusion outcomes. Income-related factors emerge as the most negatively associated with financial inclusion outcomes, with a BMA estimate of -0.571 and decisive evidence of inclusion. The influence reinforces the well-established view that income remains a fundamental barrier to accessing and meaningfully engaging in financial services. The magnitude of this effect demonstrates the economic importance of income constraints in shaping financial inclusion outcomes across diverse study contexts.

4.2.3. Estimation technique

The estimation method employed is not inconsequential. Among the estimation methods, the logit model stands out with the highest posterior inclusion probability and a positive posterior mean. We show that studies employing logistic regression tend to report more positive effects of financial inclusion. We report this as intuitive, given that logit models are commonly used to estimate binary outcomes and may better capture threshold effects that linear models overlook. By comparison, the Generalized Method of Moments (GMM) approach exhibits a relatively higher inclusion probability than the other estimates. The results of the GMM posterior mean suggest that its reported effects tend to be more conservative. GMM estimators, especially system GMM, address potential biases and inefficiencies present in dynamic panel data. The conservative feature arises from their robustness to issues like endogeneity, weak instruments, and small sample bias, which tend to cause simpler estimators to overstate effects. Ordinary least squares (OLS) methods show a more muted effect and a limited explanatory relevance. Techniques such as probit and fixed effects display lower inclusion probabilities and exert limited influence. The relatively weak performance of Fixed Effects is notable, given its strength in addressing unobserved heterogeneity (Duxbury, 2021).

4.2.4. Country and regional characteristics

The evidence on geographic characteristics reveals substantial regional heterogeneity in the financial inclusion literature. Studies focused on Sub-Saharan Africa are virtually certain to report positive financial inclusion effects, with a meaningful effect size of 0.045. The pattern suggests that financial inclusion determinants operate systematically and robustly in this region. The pattern remains consistent across the Middle East and North Africa (MENA) region. Studies focused on MENA show the largest mean effect of 0.093. In stark contrast, the evidence for Asia, Europe, Latin America, and the Caribbean is comparatively weak, with limited influence on the variation in reported estimates. Financial inclusion determinants may be less influential in these regions, potentially due to already well-developed financial systems or different underlying mechanisms driving financial inclusion. Their low PIPs explain the substantial model uncertainty about whether these regional effects exist at all. These findings may help explain the persistent disparities in financial inclusion progress across these regions, despite ongoing policy efforts.

At the country level, studies focused on both developed and developing countries exhibit high relevance, but a striking contrast in terms of financial inclusion determinants. Studies focused on developed countries demonstrate a positive relationship, which likely reflects the structures that translate these determinants into improved financial access. Studies conducted in developing economies show moderate relevance and tend to report more negative estimates. These finding aligns with expectations from the literature, which highlights the difficulties these countries face, such as limited infrastructure, weaker regulatory environments, and lower income levels (Beck, Senbet and Simbanegavi, 2015; Mukherjee and Sood, 2020). Developed countries, by comparison, exhibit more favourable financial inclusion effects, which may be attributed to mature financial ecosystems and stronger institutional support.

4.2.5. Dataset structure and type

In terms of data structure, panel data studies emerge as particularly influential. Studies employing this data structure tend to report more negative estimates. The superior capacity of panel datasets to control for unobserved heterogeneity and capture dynamic adjustment processes likely explains this pattern. These features are systematically overlooked in cross-sectional approaches. In contrast, cross-sectional and time series data structures demonstrate only weak evidence of systematic influence on reported estimates, with PIPs falling below conventional significance thresholds. Hence, while the choice between these two alternative approaches may affect

individual study results, they do constitute systematic sources of heterogeneity across the literature when controlling for other design characteristics.

Periods of financial crisis also exhibit a significant negative impact on results, which aligns with theoretical expectations and recent empirical work about the disruptive impact of crises on financial inclusion progress (Eshun and Kočenda, 2025). On the other hand, the characteristics of the data source appear to have no meaningful influence on reported outcomes. Hence, whether studies rely on international databases, household surveys, administrative data, or alternative sources, it does not fundamentally vary reported effect magnitudes when controlling for other design features.

Next, the data coverage period (the years encompassed by a study sample) shows very high importance (BMA result 0.007, PIP 1.000) with small positive effects. The years' midpoint variable (middle year of the time span covered by studies) demonstrates a positive relevance, indicating that more recent studies are systematically more likely to report positive financial inclusion effects. We highlight that the improvements in financial inclusion policies, technologies, and implementation strategies over time are likely drivers behind the more positive assessments in recent studies.

4.2.6. Publication Characteristics

The Bayesian Model Averaging (BMA) results suggest that certain publication characteristics exert minimal influence on the reported estimates of financial inclusion effects. Specifically, whether a study is published in a peer-reviewed outlet or not, as well as its year of publication, both characteristics exhibit very low posterior inclusion probabilities (PIP = 0.001 and 0.000, respectively) and negligible average effects. These findings are consistent with patterns observed in the broader meta-analytic literature, which frequently reports that neither the publication outlet nor the timing of publication systematically biases reported effect sizes (Ehrenbergerova, Bajzik and Havranek, 2023; Bortnikova, Bajzik and Kočenda, 2025).

Next, other publication metrics demonstrate notable relevance, albeit with small effect sizes. Studies with higher citation counts and those published in journals with higher influence scores tend to show some systematic variation in reported outcomes, although the effect sizes remain modest. This suggests that while journal quality and visibility may shape the dissemination of findings, they do not substantially alter the core estimates associated with determinants.

Interestingly, studies published in journals with higher impact factors tend to report slightly smaller, more conservative estimates. One possible explanation is that these journals often apply

stricter methodological standards during the review process. As a result, studies with more rigorous analysis are more likely to be accepted, and such rigour may lead to more cautious or tempered conclusions about the effects of financial inclusion. Such a pattern is consistent with the notion that higher methodological quality reduces the risk of bias and, consequently, the likelihood of overly optimistic findings (Schulz, 1995; Djulbegovic *et al.*, 2011).

5. Conclusion

This study has provided the first systematic meta-analysis of the determinants of financial inclusion, drawing on 3,817 estimates from 102 studies published between 2013 and 2024. By converting diverse results into a common unbiased metric, we have been able to reconcile conflicting evidence and establish reliable benchmarks for the true impact of inclusion drivers.

The analysis shows that while financial inclusion responds positively to a range of factors, the magnitude of these effects is smaller than suggested by individual studies once biases are accounted for. Income-related variables, often assumed to be decisive, emerge as relatively weak predictors. By contrast, technology, infrastructure, and the persistence of prior inclusion consistently display stronger and more durable impacts. Regional variation is equally striking: Sub-Saharan Africa and MENA benefit more systematically from inclusion drivers, whereas effects are weaker in Europe and parts of Asia.

These findings carry important policy implications. Relying on income growth alone will not deliver widespread financial inclusion. Instead, investment in digital finance, institutional capacity, and infrastructure is essential, especially when combined with regulatory environments that support innovation and trust. The evidence also suggests that early interventions can have lasting payoffs, as financial access tends to reinforce itself over time.

Overall, our results temper overly optimistic readings of single studies and provide policymakers with realistic benchmarks for designing strategies that advance inclusive finance. By consolidating a fragmented literature into a coherent and unbiased evidence base, the study offers clearer guidance for making financial inclusion an effective and durable contributor to development.

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TABLES

Table 1 - Publication Bias tests for the dimensions of financial inclusion

All estimates

Panel A: Linear techniques					
	OLS	MAIVE	Study	Precision	
Publication bias	0.642**	1.129***	0.732	0.713	
(Standard error)	(0.266)	(0.350)	(0.763)	(0.572)	
Effect beyond bias	0.021**	0.005	0.050	0.022*	
(Constant)	(0.009)	(0.010)	(0.033)	(0.012)	
Observations	3817	3817	3817	3817	
Panel B: Between – and within–study variation					
	BE	FE	RE		
Publication bias	1.102***	-1.920	-0.759		
(Standard error)	(0.273)	(1.366)	(0.734)		
Effect beyond bias	0.0243	0.113**	0.108***		
(Constant)	(0.017)	(0.048)	(0.036)		
Observations	3817	3817	3817		
Panel C: Nonlinear techniques					
	WAAP	Kinked model	P-uniform	Stem-based method	Selection model
Effect beyond bias	0.024***	0.026***	0.033	0.014	0.051***
	0.004	0.002	0.008	(0.014)	(0.006)
Observations	3817	3817	3817	3817	3817
Panel D: P-hacking test					
Test for monotonicity and bounds	0.608				
Test for non-increasingness	0.463				
Observations ($p \leq 0.15$)	2613				
Observations ($0.05 \leq p \leq 0.2$)	505				

*Notes: The table reports, for linear techniques, the results of regression $PCC_{is} = ySE\ (PCC_{is}) + e_{is}$ estimated for the whole sample of 3817 estimates (for which the mean estimate equals 0.044). The standard errors of the regression parameters are clustered at the study level and shown in parentheses. Panel A: OLS = ordinary least squares, MAIVE = the inverse of the square root of the number of observations used as an instrument for the standard error, Study = weighted by the inverse of the number of estimates reported per study, Precision = weighted by the inverse of the estimate's standard error. Panel B: BE = study-level between effects, FE = study-level fixed effects, RE = study-level random effects. Panel C: WAAP (weighted average of adequately powered, Ioannidis et al., 2017), kinked model (Bom and Rachinger, 2019), p-uniform (van Aert and van Assen, 2021), stem-based method (Furukawa, 2019), Selection model (Andrews and Kasy, 2019). The table reports p-values from Cox-Shi tests for detecting p-hacking (Elliott et al., 2022). ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.*

Table 2 – Description and summary statistics of variables

		Entire sample studies			Peer-reviewed studies		
Variable	**Description**	**Mean**	**Std. Dev.**	**Weighted mean**	**Mean**	**Std. Dev.**	**Weighted mean**
Financial inclusion effect	Reported estimate recomputed to represent the unbiased partial correlation coefficient (PCC) of the various determinants of financial inclusion	0.044	0.159	0.076	0.048	0.168	0.079
Standard error (SE)	Reported standard error recomputed to represent the standard error of the unbiased PCC	0.036	0.036	0.047	0.038	0.036	0.048
	Measurement of financial inclusion						
Financial inclusion index	= 1 if the dependent variable is a composite Financial Inclusion Index (FII), zero otherwise.	0.152	0.359	0.220	0.154	0.361	0.206
Access dimension	= 1 if the dependent variable captures the access dimension (e.g. number of branches), zero otherwise.	0.282	0.450	00.329	0.299	0.458	0.337
Usage dimension	= 1 if the dependent variable captures the usage dimension (e.g. bank deposits), zero otherwise.	0.450	0.497	0.369	0.447	0.497	0.374
Quality dimension	=1 if the dependent variable captures the quality dimension (e.g. insurance), zero otherwise.	0.054	0.226	0.036	0.061	0.24	0.040
Other measures	= 1 if any other measure of financial inclusion is used (e.g. inclusion programs), zero otherwise (reference category).	0.059	0.236	0.044	0.039	0.193	0.044
	Financial inclusion determinants						
Lag dependent variable	= 1 if lagged dependent variable is included in the regression or as a determinant, zero otherwise (reference category).	0.118	0.108	0.009	0.014	0.116	0.009
Macroeconomic factors	= 1 if the determinants include macroeconomic variables (e.g. inflation, interest rate), zero otherwise.	0.169	0.375	0.220	0.171	0.376	0.207
Demographic factors	= 1 if demographic factors (e.g. age, gender) are included as a determinant, zero otherwise.	0.213	0.410	0.244	0.210	0.407	0.248
Credit & financial depth	= 1 if indicators of credit and financial depth (e.g. private credit/GDP) are included, zero otherwise.	0.032	0.176	0.020	0.035	0.184	0.018
Income factors	= 1 if income-related variables (e.g. GDP per capita, income Q2) are included, zero otherwise.	0.287	0.452	0.196	0.278	0.448	0.197
Education & human capital	= 1 if education/human capital indicators are included as a determinant (e.g. literacy, primary school enrollment), zero otherwise.	0.222	0.406	0.231	0.223	0.416	0.236
Bank structure	= 1 if bank structure indicators (e.g. bank concentration) are included, zero otherwise.	0.033	0.178	0.040	0.033	0.178	0.041

Technology & infrastructure	= 1 if technology/infrastructure indicators are included (e.g. internet access), zero otherwise.	0.017	0.129	0.029	0.019	0.136	0.032
Institutional factors	= 1 if institutional or governance indicators are used (e.g. rule of law, corruption), zero otherwise.	0.015	0.122	0.011	0.018	0.134	0.013
Construction of financial inclusion							
PCA index	= 1 if the financial inclusion index is constructed using Principal Component Analysis, zero otherwise.	0.091	0.288	0.089	0.086	0.281	0.077
Others	= 1 if the financial inclusion index is constructed using other methods, zero otherwise (reference category).	0.158	0.364	0.221	0.174	0.379	0.226
Estimation technique							
Ordinary least squares (OLS)	= 1 if OLS is used as the estimation technique, zero otherwise.	0.060	0.237	0.124	0.070	0.255	0.132
Fixed effect	= 1 if the Fixed Effects estimator is used, zero otherwise.	0.037	0.188	0.074	0.021	0.143	0.063
Logit	= 1 if Logit model regression is used for estimation, zero otherwise.	0.156	0.363	0.212	0.163	0.369	0.206
Probit	= 1 if Probit model regression is used for estimation, zero otherwise.	0.505	0.500	0.347	0.489	0.500	0.356
Generalized methods of moments (GMM)	= 1 if the Generalized Method of Moments (GMM) is used for estimation, zero otherwise.	0.118	0.322	0.071	0.139	0.346	0.071
Other estimation methods	= 1 if other methods (IV method, random effect, quantile regression, 2SLS) are used for estimation (reference category for estimation methods).	0.157	0.364	0.195	0.158	0.365	0.198
Developed countries	= 1 if the country(s) of study is a or include a developed country, zero otherwise.	0.194	0.395	0.106	0.180	0.384	0.097
Developing countries	= 1 if the country(s) of study is a or include a developing country, zero otherwise.	0.471	0.499	0.587	0.453	0.498	0.584
Mixed income countries	=1 if the study covers both developed and developing countries, and zero otherwise.	0.335	0.472	0.307	0.367	0.482	0.319
Country/Region							
Asia	= 1 if the estimate's sample country(s) is in Asia and zero otherwise.	0.31	0.462	0.224	0.325	0.468	0.226
Europe	= 1 if the estimate's sample country(s) is in Europe, and zero otherwise.	0.002	0.039	0.009	0.002	0.043	0.011
Latin America & Caribbean (LAC)	= 1 if the estimate's sample country(s) is in the LAC economies, and zero otherwise.	0.054	0.227	0.048	0.052	0.222	0.042
Middle East & North Africa (MENA)	= 1 if the estimate's sample country(s) is in the MENA economies, and zero otherwise.	0.008	0.087	0.022	0.009	0.096	0.025
Sub-Saharan Africa	= 1 if the estimate's sample country(s) is in SSA, and zero otherwise.	0.342	0.474	0.446	0.374	0.484	0.475
Multi-countries/regions	= 1 if the estimate's sample country(s) fall into two or more (multiple) primary regions – Asia, Europe, LAC, MENA,	0.283	0.451	0.246	0.237	0.425	0.221

	and SSA (e.g., other Pacific Island nations), and zero otherwise (reference category for country/region).						
Data structure/type							
Years of data coverage	Length of the period under review (in years).	4.782	6.760	4.412	5.153	7.215	4.433
Beginning of period	Start year of the sample.	2012	5.910	2012	2012	6.146	2012
End of period	End year of the sample.	2015	3.224	2016	2016	3.475	2016
Average year period	Average year of the period under review.	2014	3.353	2014	2014	3.451	2014
Mid-period point	Mid-point, as the mean year of the data used minus the earliest mean year in the data	11	3	7.608	11	3	12
Data size	The logarithm of the total number of observations used to estimate the effects	7.578	2.111	7.074	7.306	1.964	6.914
Data source	= 1 if an international data source (e.g., IMF Financial Access Survey, Global Financial Development, World Development Indicator) is used, zero for local sources such as national surveys or rural surveys	0.886	0.318	0.775	0.875	0.330	0.763
Financial crisis	= 1 if the study controls for a period of financial crisis.	0.073	0.260	0.019	0.089	0.284	0.022
Time dummy	= 1 if the study controls for a time dummy.	0.035	0.185	0.057	0.043	0.203	0.065
Cross-sectional	= 1 if cross-sectional data are used.	0.519	0.500	0.517	0.489	0.500	0.530
Panel data	= 1 if panel data are used.	0.418	0.493	0.392	0.473	0.500	0.397
Time series	= 1 if time-series data are used (reference category for the group of dummy variables describing panel and cross-sectional dimension of data).	0.061	0.240	0.081	0.033	0.179	0.061
Publication characteristics							
Peer-reviewed	= 1 if published in a refereed journal or chapter in a book. We expect published studies to exhibit higher quality on average and to contain fewer mistakes in reporting their results. However, the inclusion of unpublished papers is unlikely to alleviate publication bias (Rusnák et al., 2013): researchers write their papers with the intention to publish. Otherwise, the article is a working paper (De Batz and Kočenda, 2024).	0.824	0.380	0.871	1	0	1
Year of publication	Year in which the study was published or first made publicly accessible	2019	2.812	2019	2020	2.958	2020
Log of the year of publication	Publication year, as the logarithm of the year of publication.	7.610	0.001	7.610	7.61	0.001	7.61
Journal impact factor	Journal impact factor for the journal recorded in Scopus as of the year of publication. JIF is the average number of citations received by articles	2.764	1.833	2.547	2.764	1.833	2.448

	published in the journal within a two-year period.						
Article influence score (AIS)	Article influence score of the journal, as recorded in Scopus for the year of publication. AIS measures the average importance or influence of the journal on a per-article basis. An AIS greater than 1.00 indicates that the articles in a journal have an above-average influence.	0.679	5.682	0.634	0.316	0.377	0.248
Google Scholar citation count	Total number of citations for the individual article, as recorded in Google Scholar (counted as a raw number)	76.512	181.446	96.002	88.405	197.263	105
Log of Google Scholar citation	Logarithm of the number of citations of the study since its first appearance on Google Scholar.	2.858	1.801	3.236	2.974	1.874	3.351

Notes: SD = standard deviation, WM = mean weighted by the inverse of the number of estimates reported per study.

Table 3 – Why Estimates Vary

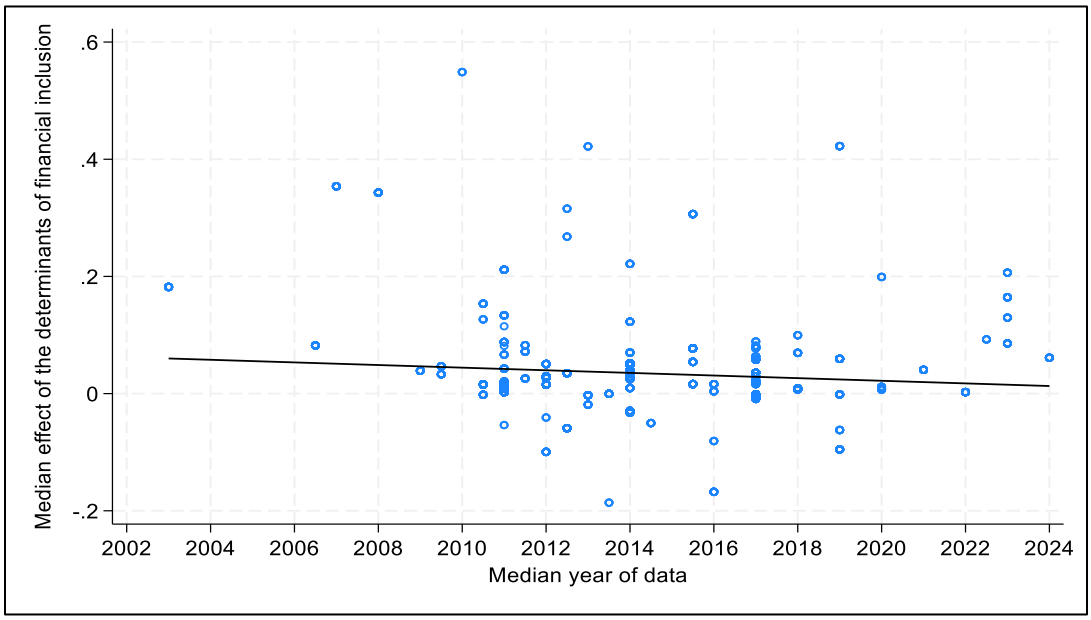
Response variable: Financial Inclusion	Bayesian model averaging (baseline model)			Frequentist check (OLS)			Frequentist model averaging (robustness check)		
	P. mean	P.SD	PIP	Coeff.	Std. error	Pvalue	Coeff.	Std. error	Pvalue
Constant	0.66	N/A	1.000	0.568	0.122	0.000	7.170	3.600	0.046
Standard Error	0.384	0.086	0.997	0.028	0.324	0.931	0.320	0.085	0.000
Measurement of financial inclusion									
Financial inclusion index	0.000	0.001	0.020				0.034	0.012	0.006
Access dimension	0.001	0.004	0.117				0.037	0.011	0.001
Usage dimension	0.000	0.001	0.021				0.029	0.010	0.005
Quality dimension	0.000	0.002	0.019				0.034	0.014	0.016
PCA Index	-0.010	0.015	0.352				-0.024	0.011	0.024
Financial inclusion determinants									
Macroeconomic factors	-0.546	0.022	1.000	-0.596	0.123	0.000	-0.549	0.022	0.000
Demographic factors	-0.553	0.022	1.000	-0.637	0.114	0.000	-0.557	0.022	0.000
Credit & Financial Depth	-0.568	0.024	1.000	0.585	0.127	0.000	-0.573	0.025	0.000
Income factors	-0.570	0.022	1.000	-0.645	0.114	0.000	-0.571	0.022	0.000
Education & human capital	-0.528	0.022	1.000	-0.609	0.114	0.000	-0.531	0.022	0.000
Bank structure	-0.533	0.025	1.000	-0.556	0.095	0.000	-0.534	0.025	0.000
Technology & infrastructure	-0.428	0.028	1.000	-0.405	0.144	0.005	-0.433	0.028	0.000
Institutional factors	-0.550	0.028	1.000	-0.577	0.119	0.000	-0.555	0.028	0.000
Estimation technique									
Ordinary least squares	0.005	0.012	0.191				0.018	0.012	0.115
Fixed effect	-0.021	0.024	0.488				-0.033	0.015	0.025
Logit	0.031	0.016	0.832	0.039	0.027	0.158	0.027	0.011	0.011
Probit	-0.006	0.013	0.214				-0.010	0.010	0.322
Generalized Methods of Moments	-0.029	0.020	0.753				-0.030	0.012	0.011
Country/Region									
Asia	0.000	0.001	0.023				-0.006	0.008	0.468
Europe	-0.001	0.009	0.019				-0.040	0.057	0.488
Latin America & Caribbean	0.000	0.002	0.025				-0.003	0.013	0.842
Middle East & North Africa	0.093	0.034	0.943	0.014	0.033	0.680	0.083	0.027	0.002
Sub-Saharan Africa	0.045	0.007	1.000	0.041	0.019	0.032	0.039	0.008	0.000
Developed countries	0.030	0.014	0.895	0.069	0.017	0.000	0.033	0.008	0.000
Developing countries	-0.020	0.014	0.747				-0.021	0.008	0.010
Data structure/type									
Data source	0.000	0.002	0.022				0.003	0.008	0.757
Years of Data Coverage	0.007	0.001	1.000	0.003	0.004	0.413	0.009	0.001	0.000
Years Midpoint	0.003	0.002	0.891	0.005	0.003	0.068	0.006	0.002	0.000
Financial crisis	-0.088	0.021	0.999	-0.040	0.053	0.453	-0.093	0.017	0.000
Cross-sectional	-0.003	0.009	0.143				-0.027	0.010	0.010
Panel data	-0.031	0.018	0.845	-0.039	0.034	0.252	-0.057	0.012	0.000
Publication characteristics									

Peer-reviewed	0.001	0.005	0.094				0.015	0.008	0.064
Journal impact factor	-0.007	0.003	0.942	-0.007	0.004	0.093	-0.007	0.002	0.000
Article influence score	0.000	0.000	0.895	0.000	0.000	0.004	0.000	0.000	0.000
Google Scholar citation	0.000	0.000	1.000	0.000	0.000	0.233	0.000	0.000	0.000
Year of Publication	0.000	0.001	0.042				-0.003	0.002	0.067
Studies	102			102			102		
Observations	3,817			3,817			3,817		

Notes: In Bayesian Model Averaging (BMA), the posterior mean denotes the partial derivative of the reported determinant effect with respect to the corresponding study characteristic. P. mean = posterior mean, P. SD = posterior standard deviation, PIP = posterior inclusion probability, SE = standard error. BMA employs the unit information prior recommended by Eicher et al. (2011) and the dilution prior suggested by George (2010), which accounts for collinearity. The frequentist check (stepwise regression) is estimated using the 5% significance threshold and standard errors clustered at the study level. All variables are described in Table 2. Technical details and diagnostics of the BMA exercise are available in Table A4 and Figure B5.

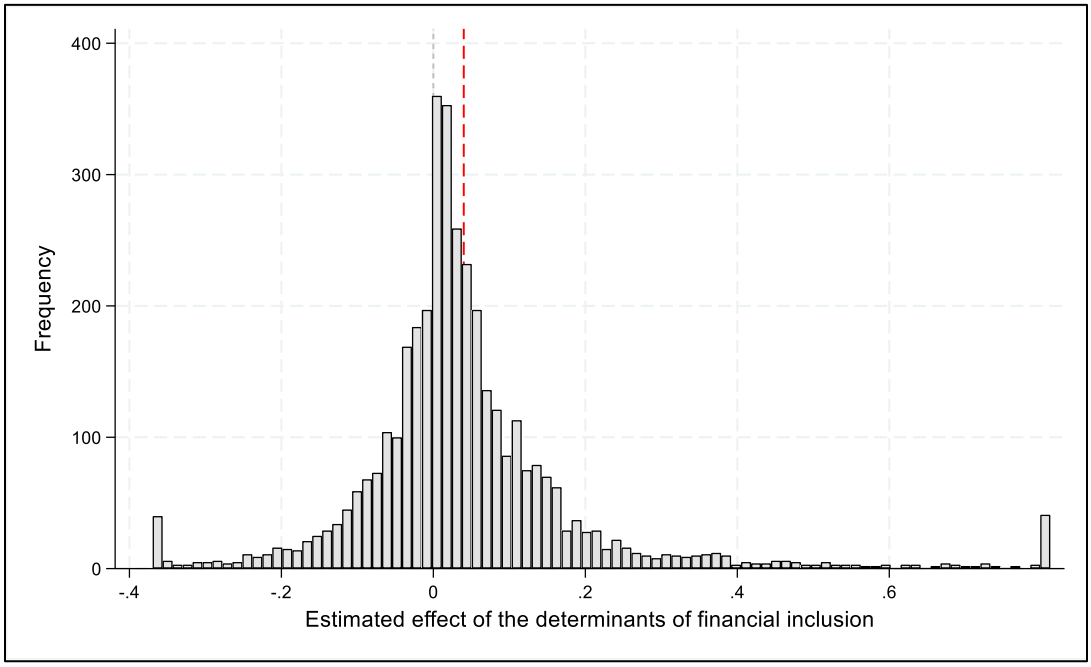
FIGURES

Figure 1 - Median estimated effect in the literature



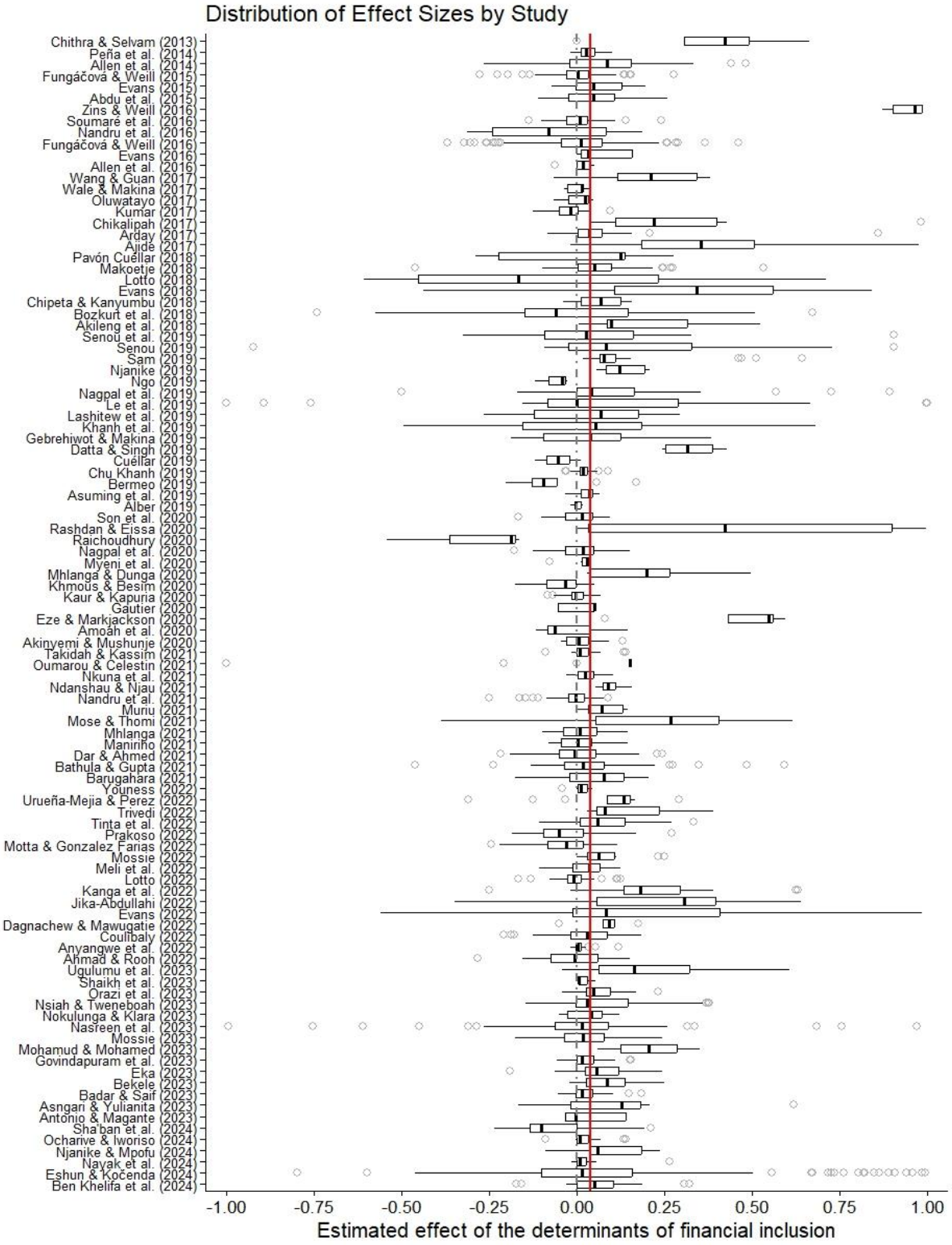
The median and variance of reported elasticities decrease over time. Notes: The vertical axis measures the median of the estimated effect on financial inclusion reported in individual studies. The horizontal axis measures the median year of the data used in the corresponding study.

Figure 2 - Histogram of effect distribution



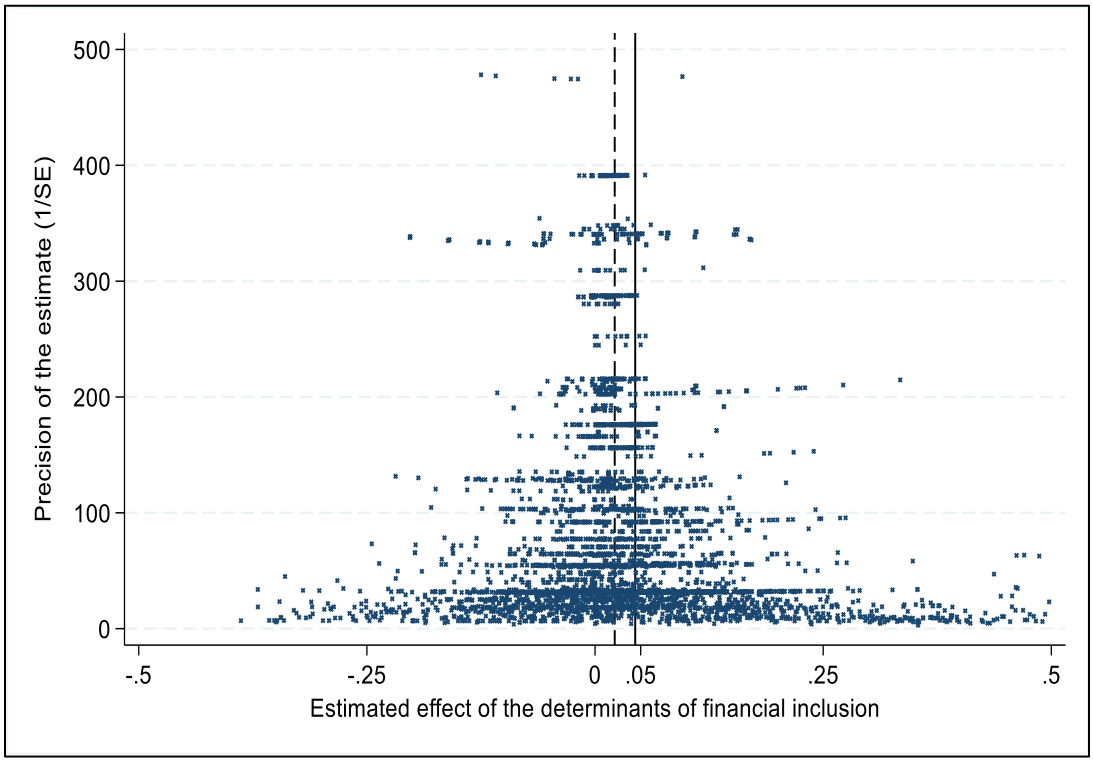
Notes: The figure depicts a histogram of the estimated effects of financial inclusion in individual studies. The grey vertical line represents zero. The mean reported effect is denoted as a red broken vertical line.

Figure 3 - Box Plot of the estimated effects of the determinants of financial inclusion per study



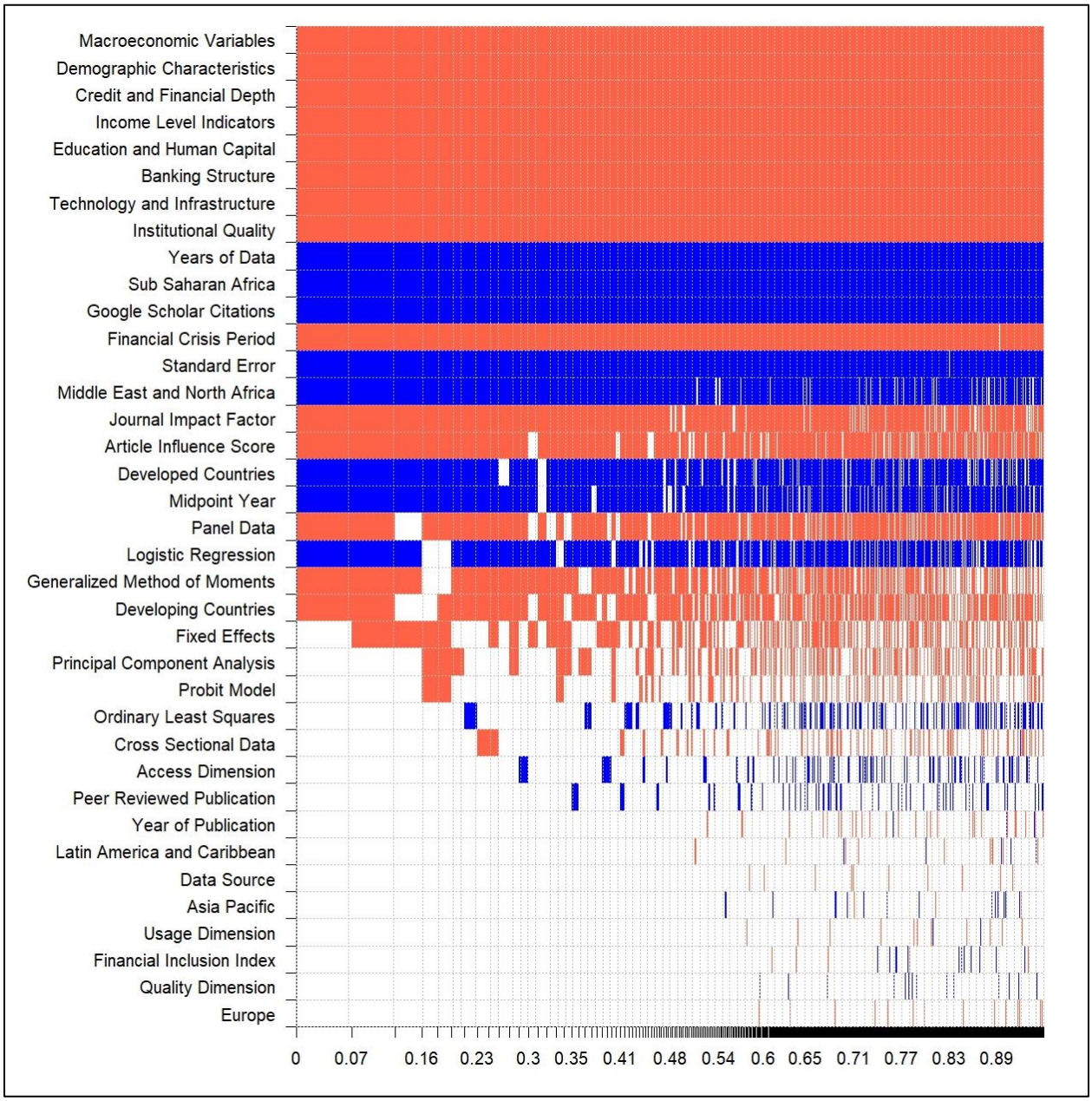
Notes: The figure shows a box plot of the reported estimate of financial inclusion. Studies are sorted by age from the oldest to the newest. All estimates are recomputed to represent the unbiased partial correlation coefficient (PCC) of the various determinants of financial inclusion. The whiskers represent the highest and lowest data points in the study. The mean effect is denoted as a solid red vertical line.

Figure 4 - The funnel plot suggests slight publication bias



Notes: The solid vertical line represents the mean estimate, and the dashed vertical line represents the median estimate. In the absence of publication bias, the scatter plot should resemble an inverted funnel symmetrical around the mean. For ease of exposition, outliers are excluded from the figure but included in all statistical tests.

Figure 5 – Baseline Model inclusion in Bayesian model averaging



Notes: The figure depicts the results of the benchmark BMA model reported in the Table below. We employ the unit information g-prior (the prior has the same weight as one observation of data) recommended by Eicher et al. (2011) and the dilution prior suggested by George (2010), which accounts for collinearity. The explanatory variables are ranked according to their posterior inclusion probabilities from the highest at the top to the lowest at the bottom. The horizontal axis shows the values of the cumulative posterior model probability. Blue colour (darker in grayscale) = the estimated parameter of the corresponding explanatory variable is positive. Red colour (lighter in grayscale) = the estimated parameter of the corresponding explanatory variable is negative. No colour = the corresponding explanatory variable is not included in the model. Numerical results are reported in Table 2. Technical details and diagnostics of the BMA exercise are available in Table A4 and Figure B5.

Appendix A

Appendix Table A1 - Studies included in the meta-analysis

Author and Year	Author and Year	Author and Year
Abdu et al. (2015)	Evans (2018)	Nasreen et al. (2023)
Ahmad & Rooh (2022)	Evans (2022)	Nayak et al. (2024)
Ajide (2017)	Eze & Markjackson (2020)	Ndanshau & Njau (2021)
Akileng et al. (2018)	Fungáčová & Weill (2015)	Ngo (2019)
Akinyemi & Mushunje (2020)	Fungáčová & Weill (2016)	Njanike (2019)
Alber (2019)	Gautier et al. (2020)	Njanike & Mpofu (2024)
Allen et al. (2014)	Gebrehiwot & Makina (2019)	Nkuna et al. (2021)
Allen et al. (2016)	Govindapuram et al. (2023)	Nokulunga & Klara (2023)
Amoah et al. (2020)	Jika-Abdullahi (2022)	Nsiah & Tweneboah (2023)
Antonio & Magante (2023)	Kanga et al. (2022)	Ocharive & Iworiso (2024)
Anyangwe et al. (2022)	Kaur & Kapuria (2020)	Oluwatayo (2017)
Arday (2017)	Khanh et al. (2019)	Orazi et al. (2023)
Asngari & Yulianita (2023)	Khmous & Besim (2020)	Oumarou & Celestin (2021)
Asuming et al. (2019)	Kumar (2017)	Pavón Cuéllar (2018)
Badar & Saif (2023)	Lashitew et al. (2019)	Pena et al. (2014)
Barugahara (2021)	Le et al. (2019)	Prakoso (2022)
Bathula & Gupta (2021)	Lotto (2018)	Raichoudhury (2020)
Bekele (2023)	Lotto (2022)	Rashdan & Eissa (2020)
Ben Khelifa et al. (2024)	Makoetje (2018)	Sam (2019)
Bermeo (2019)	Maniriho (2021)	Senou et al. (2019a)
Bozkurt et al. (2018)	Meli et al. (2022)	Senou et al. (2019b)
Chikalipah (2017)	Mhlanga (2021)	Sha'ban et al. (2024)
Chipeta & Kanyumbu (2018)	Mhlanga & Dunga (2020)	Shaikh et al. (2023)
Chithra & Selvam (2013)	Mohamud & Mohamed (2023)	Son et al. (2020)
Chu Khanh (2019)	Mose & Thomi (2021)	Soumaré et al. (2016)
Coulibaly (2022)	Mossie (2022)	Takidah & Kassim (2021)
Cuéllar (2019)	Mossie (2023)	Tinta et al. (2022)
Dagnachew & Mawugatie (2022)	Motta & Gonzalez Farias (2022)	Trivedi (2022)
Dar & Ahmed (2021)	Muriu (2021)	Ugulumu et al. (2023)
Datta & Singh (2019)	Myeni et al. (2020)	Urueña-Mejia & Perez (2022)
Eka (2023)	Nagpal et al. (2019)	Wale & Makina (2017)
Eshun & Kočenda (2024)	Nagpal et al. (2020)	Wang & Guan (2017)
Evans (2015)	Nandru et al. (2016)	Youness (2022)
Evans (2016)	Nandru et al. (2021)	Zins & Weill (2016)

Notes: Details on the literature search and inclusion criteria are provided in Appendix Figure B1. The search was completed in December 2024.

Appendix Table A2 – Descriptives of Financial Inclusion elasticities for different subsets of data

		Unweighted			Weighted		
	Est.	Mean	95% conf. int.		Mean	95% conf. int.	
Measurement of financial inclusion							
Financial inclusion index	587	0.083	0.066	0.101	0.096	0.079	0.112
Access dimension	1,062	0.055	0.044	0.066	0.077	0.065	0.090
Usage dimension	1,724	0.027	0.021	0.032	0.056	0.048	0.063
Quality dimension	203	0.044	0.019	0.070	0.128	0.090	0.165
Other measures	227	0.037	0.016	0.057	0.106	0.073	0.139
Financial inclusion determinants							
Lag dependent variable	46	0.582	0.498	0.665	0.454	0.352	0.556
Macroeconomic factors	632	0.056	0.041	0.070	0.073	0.056	0.090
Demographic factors	799	0.029	0.021	0.037	0.044	0.034	0.054
Credit & Financial Depth	120	0.023	-0.007	0.054	0.103	0.060	0.147
Income factors	1,106	0.010	0.003	0.016	0.023	0.014	0.031
Education & human capital	864	0.058	0.047	0.068	0.122	0.107	0.137
Bank structure	126	0.070	0.041	0.098	0.119	0.084	0.155
Technology & infrastructure	65	0.182	0.121	0.242	0.171	0.111	0.231
Institutional factors	59	0.036	0.000	0.072	0.037	-0.005	0.079
Construction of financial inclusion							
PCA Index	350	0.076	0.530	0.099	0.094	0.074	0.114
Others	603	0.081	0.065	0.098	0.116	0.095	0.137
Estimation technique							
Ordinary least squares	228	0.120	0.091	0.149	0.156	0.123	0.189
Fixed effect	143	0.032	0.002	0.062	0.008	-0.021	0.037
Logit	593	0.059	0.047	0.071	0.101	0.082	0.119
Probit	1,933	0.018	0.014	0.023	0.036	0.031	0.041
Generalized Methods of Moments	440	0.063	0.043	0.084	0.056	0.038	0.074
Other method	597	0.081	0.063	0.099	0.120	0.101	0.139
Developed countries	744	0.047	0.036	0.058	0.077	0.063	0.092
Developing countries	1,809	0.033	0.028	0.039	0.060	0.053	0.068
Mixed income countries	1,264	0.06	0.049	0.072	0.107	0.094	0.121
Country/Region							
Asia	1,190	0.028	0.021	0.036	0.035	0.025	0.045
Europe	6	0.013	-0.035	0.060	0.013	-0.035	0.06
Latin America & Caribbean	212	0.009	-0.002	0.019	0.021	0.011	0.031
Middle East & North Africa	25	0.140	-0.001	0.281	0.187	0.036	0.337
Sub-Saharan Africa	1,291	0.057	0.048	0.066	0.090	0.08	0.101
Multi-countries/regions	1,087	0.053	0.042	0.064	0.094	0.081	0.108
Data structure/type							
International data source	3,383	0.045	0.040	0.051	0.081	0.074	0.087
Local data source	434	0.040	0.027	0.053	0.060	0.042	0.078
Financial crisis	271	0.057	0.026	0.088	0.002	-0.024	0.028
Time dummy	137	0.086	0.043	0.129	0.210	0.157	0.263
Cross-sectional	1,992	0.028	0.023	0.033	0.057	0.050	0.064

Panel data	1,583	0.060	0.050	0.070	0.081	0.070	0.092
Time series	237	0.083	0.059	0.108	0.184	0.147	0.220
Publication characteristics							
Peer-reviewed	3,137	0.048	0.042	0.054	0.079	0.072	0.087
Non-peer-reviewed	680	0.030	0.022	0.038	0.056	0.045	0.067
All estimates	**3,817**	**0.044**	**0.040**	**0.050**	**0.076**	**0.070**	**0.082**

Appendix Table A3 – Bayesian Model Averaging and Frequentist Model Averaging for Peer-Reviewed Studies

Response variable: Financial Inclusion	Bayesian model averaging (baseline model)			Frequentist check (OLS)			Frequentist model averaging (robustness check)		
	P. mean	P.SD	PIP	Coeff.	Std. error	Pvalue	Coeff.	Std. error	Pvalue
Constant	6.125	N/A	1.000		-11.525	3.231	0.000		13.031
Standard Error	0.001	0.016	0.020						
Measurement of financial inclusion									
Financial inclusion index	0.000	0.002	0.022				0.040	0.016	0.012
Access dimension	0.011	0.010	0.628				0.055	0.015	0.000
Usage dimension	0.000	0.002	0.047				0.038	0.015	0.012
Quality dimension	0.000	0.002	0.023				0.045	0.019	0.016
PCA Index	-0.011	0.017	0.355				-0.027	0.013	0.030
Financial inclusion determinants									
Macroeconomic factors	-0.563	0.023	1.000	-0.605	0.025	0.000	-0.567	0.023	0.000
Demographic factors	-0.565	0.024	1.000	-0.630	0.026	0.000	-0.569	0.024	0.000
Credit & Financial Depth	-0.580	0.026	1.000	-0.614	0.027	0.000	-0.585	0.026	0.000
Income factors	-0.583	0.024	1.000	-0.633	0.025	0.000	-0.589	0.024	0.000
Education & human capital	-0.530	0.024	1.000	-0.605	0.025	0.000	-0.534	0.024	0.000
Bank structure	-0.542	0.027	1.000	-0.548	0.029	0.000	-0.547	0.027	0.000
Technology & infrastructure	-0.450	0.029	1.000	-0.424	0.036	0.000	-0.458	0.030	0.000
Institutional factors	-0.569	0.029	1.000	-0.596	0.032	0.000	-0.577	0.029	0.000
Estimation technique									
Ordinary least squares	0.003	0.008	0.111				0.021	0.013	0.100
Fixed effect	-0.014	0.025	0.291				-0.049	0.022	0.028
Logit	0.000	0.003	0.028				-0.004	0.013	0.783
Probit	-0.034	0.009	0.990	-0.039	0.009	0.000	-0.035	0.013	0.006
Generalized Methods of Moments	-0.015	0.021	0.402				-0.028	0.015	0.059
Country/Region									
Asia	-0.001	0.004	0.049				-0.019	0.011	0.072
Europe	-0.001	0.012	0.024				-0.069	0.060	0.248
Latin America & Caribbean	-0.001	0.005	0.042				-0.007	0.016	0.652
Middle East & North Africa	0.112	0.035	0.973	-0.004	0.011	0.752	0.087	0.031	0.005
Sub-Saharan Africa	0.061	0.008	1.000	0.014	0.009	0.067	0.050	0.010	0.000
Developed countries	0.018	0.016	0.606				0.035	0.010	0.001
Developing countries	-0.051	0.011	1.000	-0.029	0.009	0.001	-0.039	0.010	0.000
Data structure/type									
Data source	0.001	0.004	0.052				0.016	0.010	0.103
Years of Data Coverage	0.008	0.001	1.000	0.001	0.001	0.513	0.011	0.001	0.000
Midpoint Year	0.005	0.002	0.932	0.006	0.002	0.000	0.008	0.002	0.000
Financial crisis	-0.108	0.019	1.000	-0.026	0.019	0.161	-0.122	0.019	0.000
Cross-sectional	-0.044	0.022	0.878	-0.073	0.022	0.001	-0.056	0.015	0.000
Panel data	-0.103	0.021	1.000	-0.105	0.022	0.000	-0.114	0.017	0.000
Publication characteristics									
Journal impact factor	-0.001	0.003	0.117				-0.002	0.004	0.674

Article influence score	-0.053	0.022	0.902	-0.000	0.000	0.000	-0.040	0.022	0.066
Google Scholar citation	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Year of Publication	-0.003	0.003	0.517				-0.006	0.002	0.003
Studies	102			102			102		
Observations	3,069			3,069			3,069		

Notes: In Bayesian Model Averaging (BMA), the posterior mean denotes the partial derivative of the reported determinant effect with respect to the corresponding study characteristic. P. mean = posterior mean, P. SD = posterior standard deviation, PIP = posterior inclusion probability, SE = standard error. BMA employs the unit information prior recommended by Eicher et al. (2011) and the dilution prior suggested by George (2010), which accounts for collinearity. The frequentist check (stepwise regression) is estimated using the 5% significance threshold and standard errors clustered at the study level. All variables are described in Table 2. Technical details and diagnostics of the BMA exercise are available in Table A5 and Figure B6.

Table A4: Diagnostics of the baseline BMA estimation (UIP and Uniform priors)

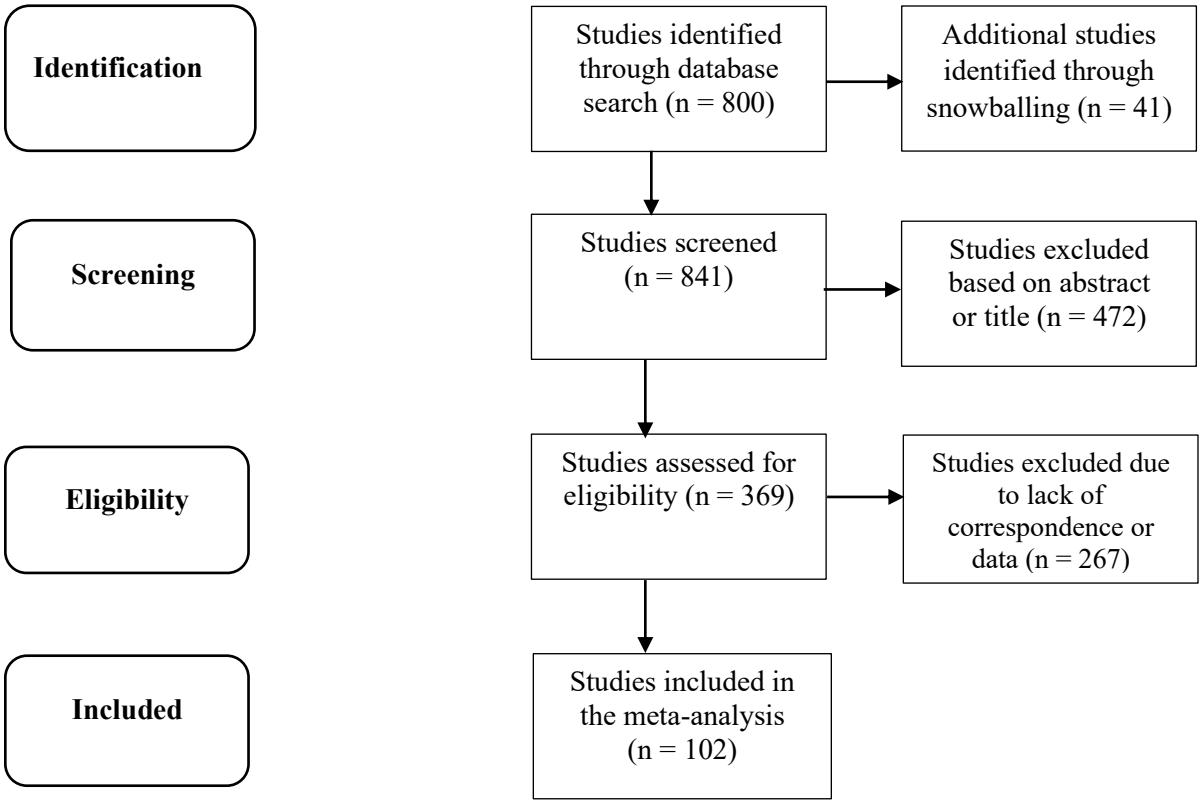
Mean no. regressors	***Draws***	***Burn-ins***	***Time***	***Shrinkage -Stats***
22.751	5,000,000	1,000,000	6.25 minutes	Avg=0.9997
No. models visited	***Modelspace***	***Visited***	***Topmodels***	
620,360	1.4 · 1011	0.00%	96%	
Correlation of PMP	***No. observation***	***Model Prior***	***g-Prior***	
0.9997	3,817	Uniform / 18.5	UIP	

Table A5: Diagnostics of peer-reviewed studies BMA estimation (UIP and Uniform priors)

Mean no. regressors	***Draws***	***Burn-ins***	***Time***	***Shrinkage -Stats***
22.011	5,000,000	1,000,000	3.72 minutes	Avg=0.9997
No. models visited	***Modelspace***	***Visited***	***Topmodels***	
809,920	$6.9 \cdot 10^{10}$	0.00%	97%	
Correlation of PMP	***No. observation***	***Model Prior***	***g-Prior***	
0.9997	3,069	Uniform / 18	UIP	

Appendix B

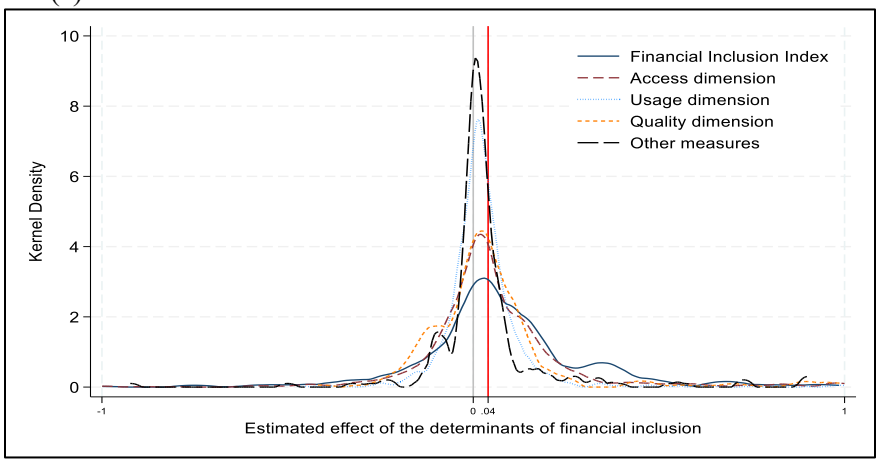
Figure B1 – Details of Literature Search (PRISMA Flow Diagram)



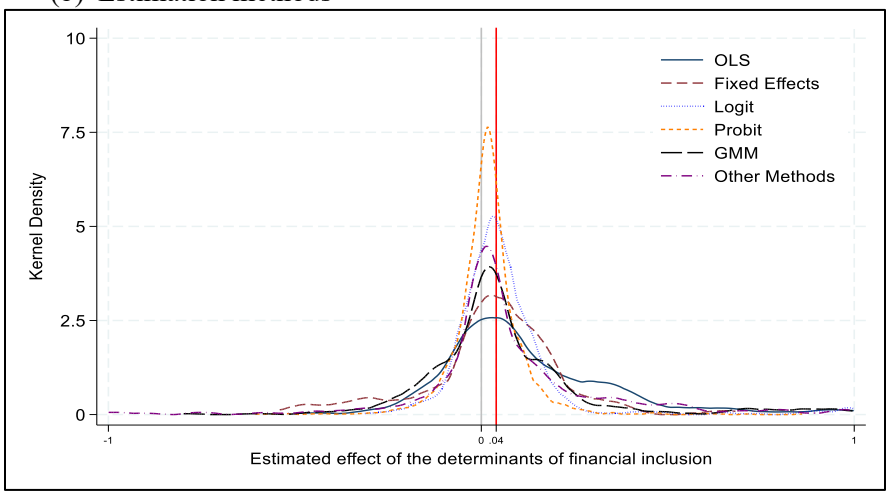
Note: The figure presents a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram illustrating the process we followed to identify the relevant estimates from primary studies included in the sample.

Appendix Figure B1 - Selected Patterns in the Literature

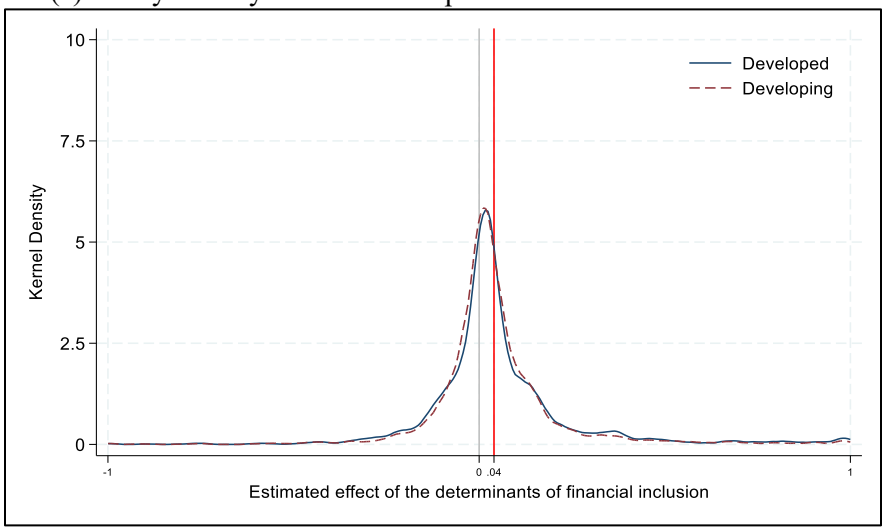
(a) Measurements of financial inclusion



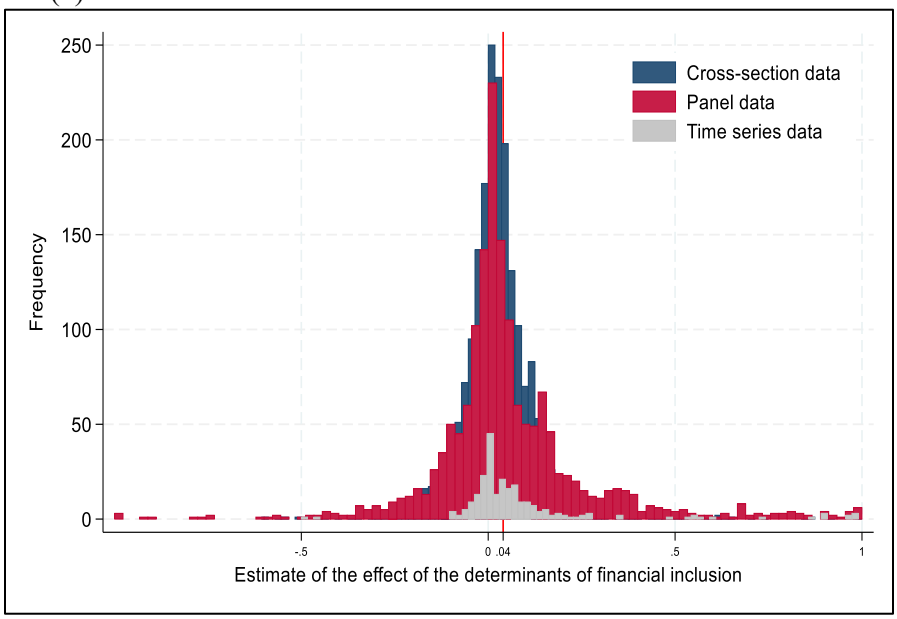
(b) Estimation methods



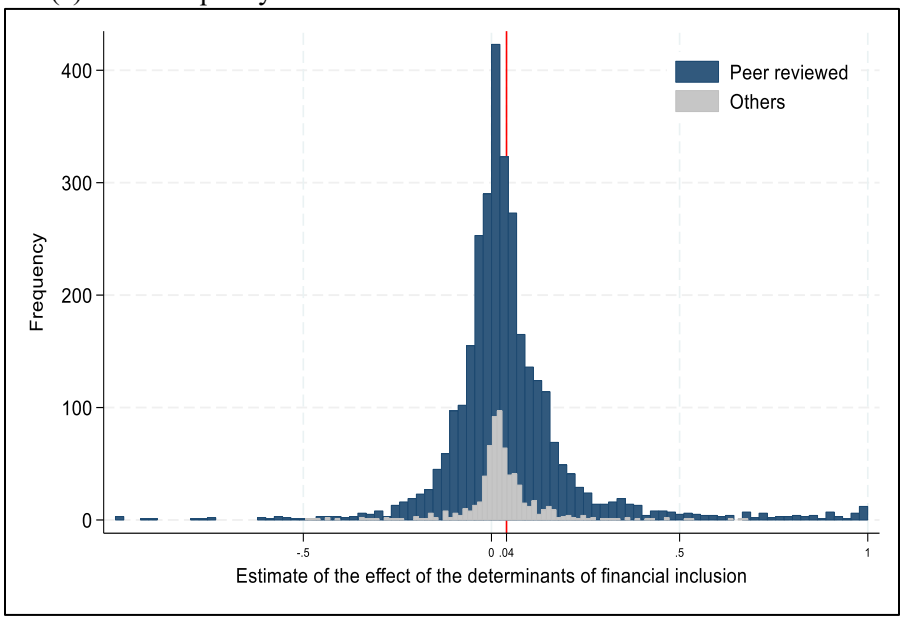
(c) Study country level of development



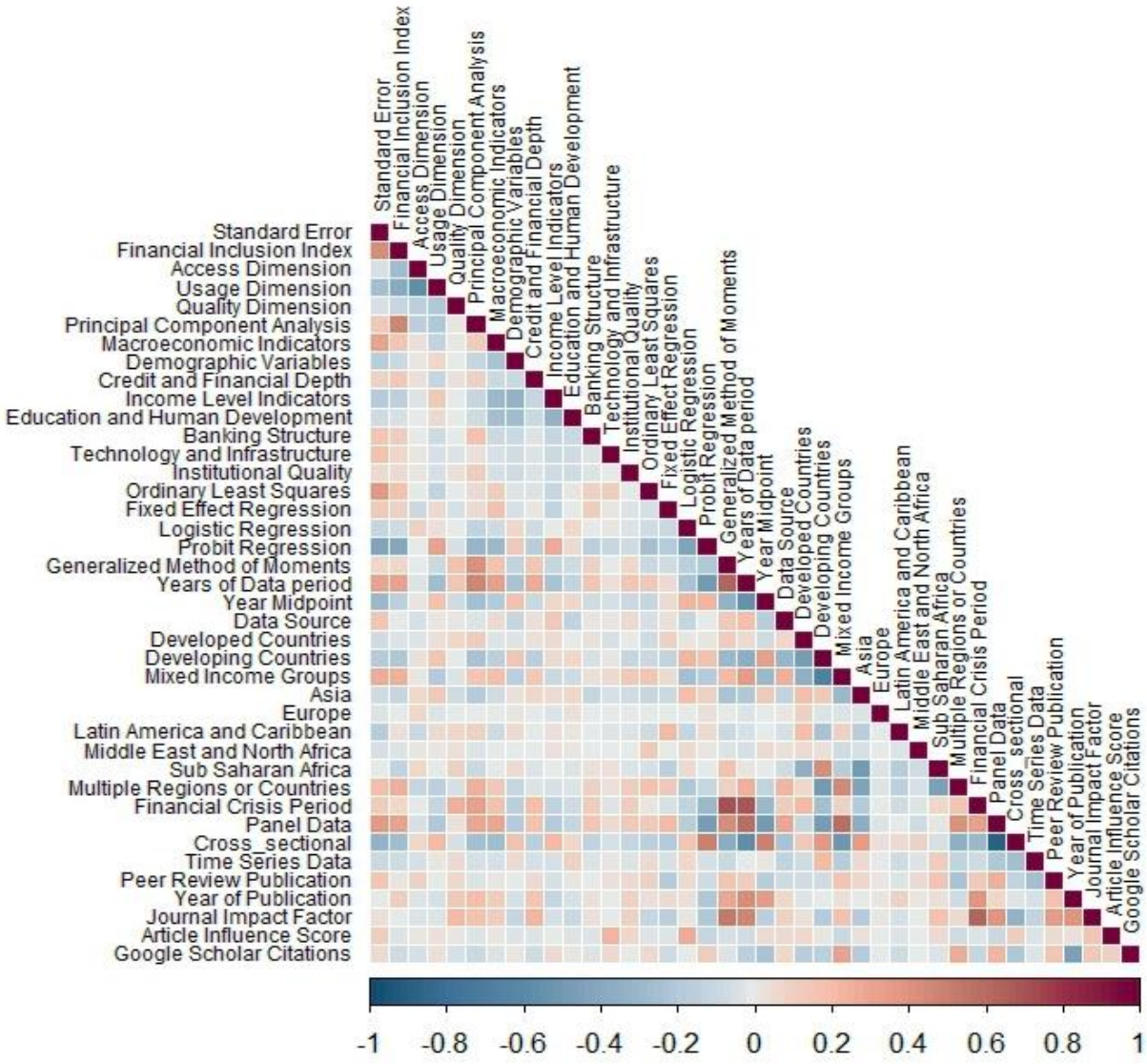
(d) Data dimension



(e) Journal quality

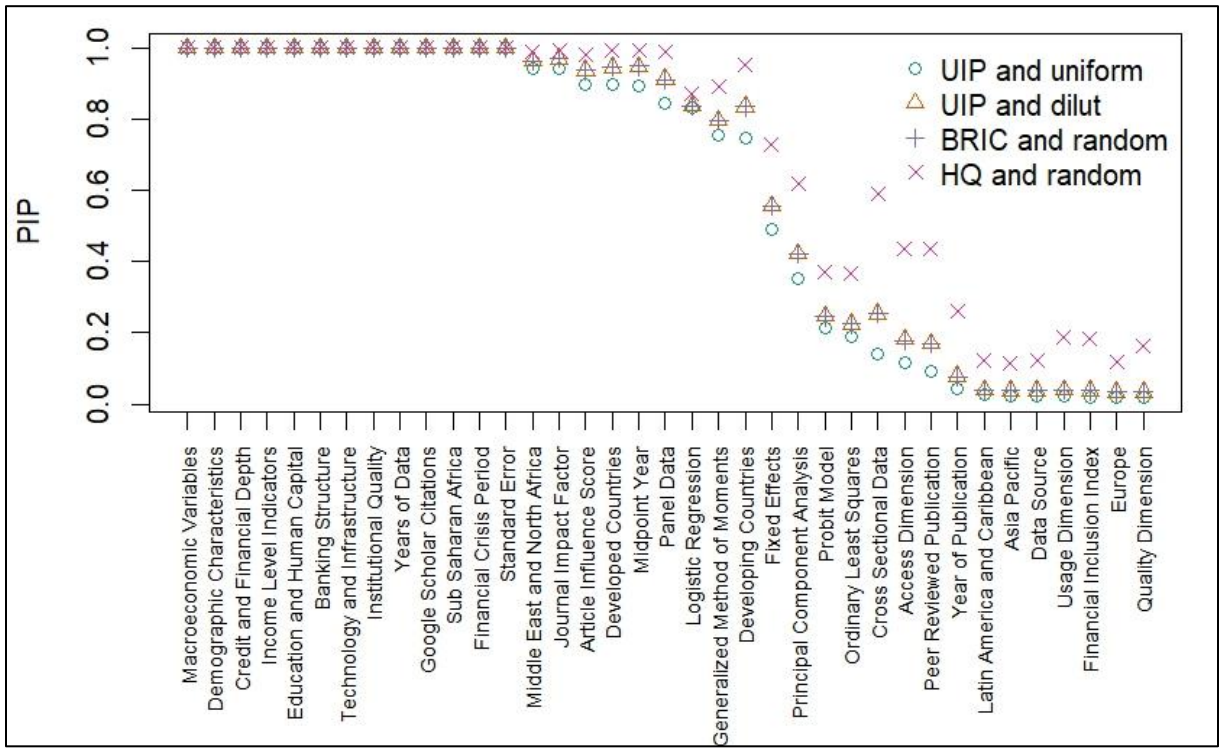


Appendix Figure B2 – Correlation Matrix Plot



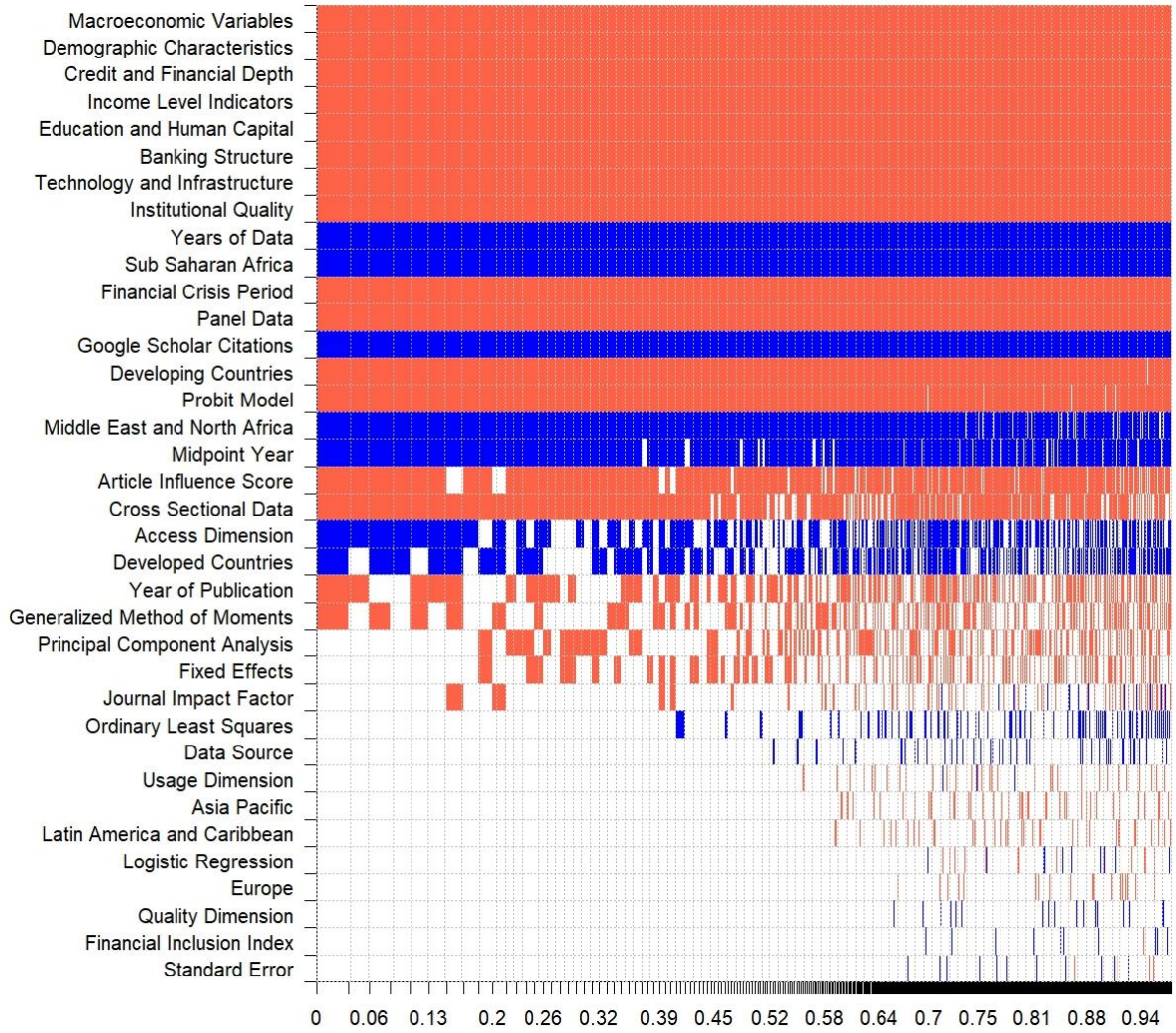
Note: The figure shows Pearson correlation coefficients for the explanatory variables in the baseline BMA model.

Appendix Figure B3: Sensitivity of Posterior Inclusion Probabilities (PIPs) to Alternative g-Priors and Model Priors in BMA



Note: This figure shows the Posterior Inclusion Probabilities (PIPs) of all covariates under different combinations of g-priors and model priors. The four combinations tested are: UIP & Uniform, UIP & Dilut, BRIC & Random, and HQ & Random. The goal is to test the robustness of the baseline results to prior assumptions.

Appendix Figure B4 – Model inclusion in Bayesian model averaging for peer-reviewed studies



Notes: The figure depicts the results of the BMA for estimates from peer-reviewed studies. The explanatory variables are ranked according to their posterior inclusion probabilities from the highest at the top to the lowest at the bottom. The horizontal axis shows the values of the cumulative posterior model probability. Blue colour (darker in grayscale) = the estimated parameter of the corresponding explanatory variable is positive. Red colour (lighter in grayscale) = the estimated parameter of the corresponding explanatory variable is negative. No colour = the corresponding explanatory variable is not included in the model. Numerical results are reported in the Appendix Table A3.

Figure B5: Model size and convergence of the baseline BMA estimation (UIP and Uniform priors)

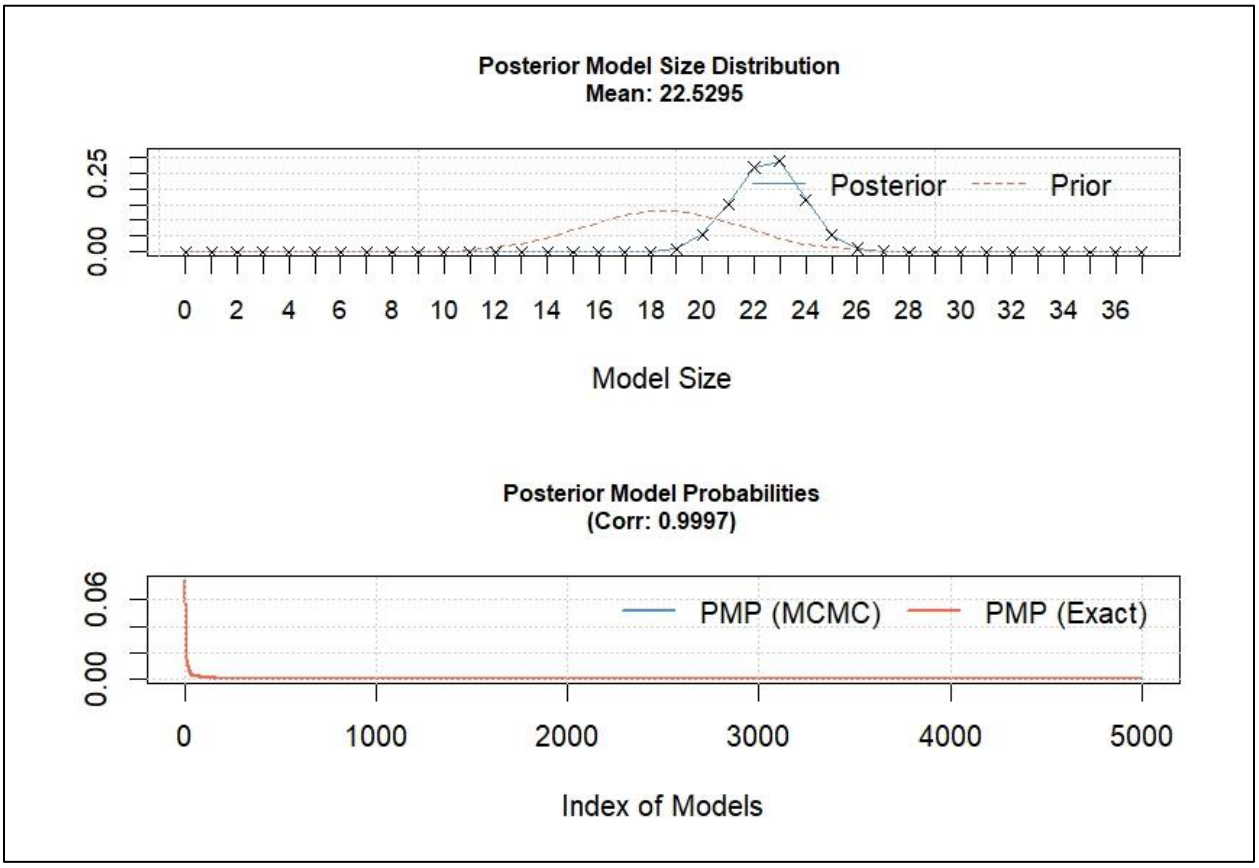
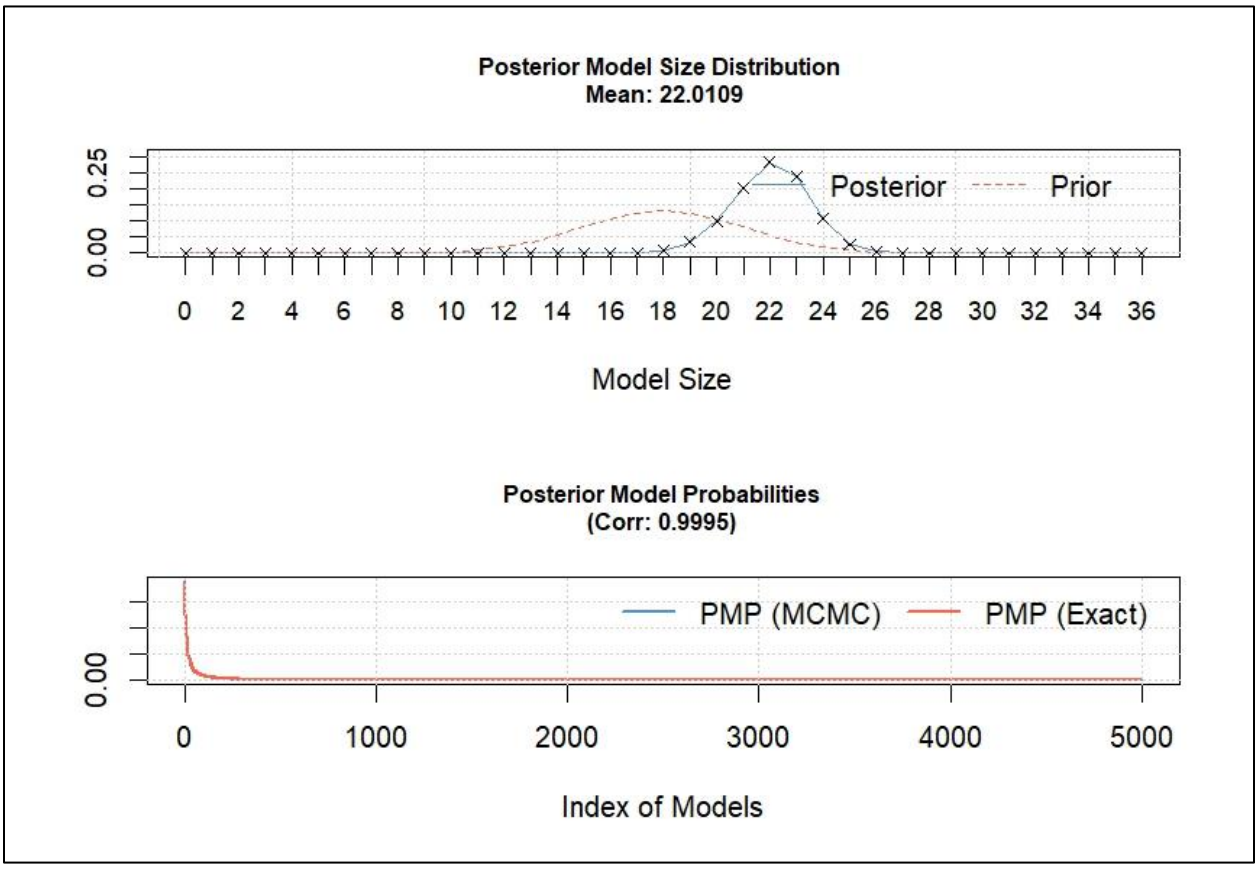


Figure B6: Model size and convergence of BMA estimation (UIP and Uniform priors) for peer-reviewed studies



Appendix C

Reference List of Studies Subject to Meta-analysis

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