ORIGINAL PAPER

DOI: 10.26794/2308-944X-2025-13-4-95-107
UDC 330.35,330.43,336.711,330.356(045)
JEL O16, G21, C11, C83

Bayesian Versus Classical Perspectives: Does Financial Inclusion Truly Drive Economic Growth?

M.N.I. Afzal
University of Southern Queensland, Sylhet, Bangladesh;
Hamdan Bin Mohammed Smart University, Dubai, UAE

ABSTRACT

Objectives: This study synthesizes quantitative evidence on the relationship between financial inclusion (FI) and economic growth (EG) to estimate the overall effect size, comparing classical (frequentist) and Bayesian meta-analytic approaches to understand how methodological choices influence the interpretation of the FI-EG nexus. **Methods:** A meta-analysis of 27 studies was conducted. Effect sizes (Fisher's z) were pooled using classical random-effects and Bayesian hierarchical models. Heterogeneity was assessed using Cochran's Q, I^2, and τ estimators (classical), as well as posterior τ distributions with Bayes factors (Bayesian). **Results:** Both approaches confirm significant positive FI-EG relationships (classical: 0.682, 95% CI [0.582, 0.782]; Bayesian: 0.616, 95% CrI [0.342, 0.824]). Substantial heterogeneity was detected (classical $\tau = 0.076$; Bayesian $\tau = 0.195$, $BF_1 > 1000$), with Bayesian analysis suggesting larger variation magnitude. **Conclusion:** Financial inclusion has a significant impact on economic growth. However, substantial heterogeneity indicates context-dependent impacts, requiring tailored policies. The Bayesian framework provides a richer characterization of uncertainty, offering more conservative and realistic evidence assessment.

Keywords: financial inclusion; economic growth; meta-analysis; Bayesian meta-analysis; heterogeneity; economic development; evidence synthesis; policy implications; frequentist statistics; quantitative synthesis

For citation: **Afzal M.N.I. Bayesian versus classical perspectives: Does financial inclusion truly drive economic growth? *Review of Business and Economics Studies*. 2025;13(4):95-107. DOI: 10.26794/2308-944X-2025-13-4-95-107**

ОРИГИНАЛЬНАЯ СТАТЬЯ

Сравнение Байесовского и классического подходов: способствует ли доступность финансовых услуг экономическому росту?

М.Н.И. Афзал
Университет Южного Квинсленда, Силхет, Бангладеш
Университет Хамдана Бин Мохаммеда Смарт, Дубай, Объединенные Арабские Эмираты

АННОТАЦИЯ

Цели: в данном исследовании обобщаются количественные данные о взаимосвязи между финансовой доступностью и экономическим ростом для оценки величины эффекта, сравнивая классический (частотный) и байесовский метааналитические подходы, чтобы понять, как методологические решения влияют на интерпретацию взаимосвязи финансовой доступности и экономического роста. **Методы:** был проведен метаанализ 27 исследований. Величины эффектов (z-критерий Фишера) были объединены с использованием классических моделей случайных эффектов и байесовских иерархических моделей. Гетерогенность оценивалась с использованием Q-критерия Кохрена, индекса I^2 и τ-оценок (классических), а также апостериорных распределений τ с байесовскими факторами (байесовский подход). **Результаты:** оба подхода подтверждают значимые положительные взаимосвязи между финансовой доступностью и экономическим ростом (классический метод: 0,682, доверительный интервал 95% [0,582, 0,782]; байесовский метод: 0,616, байесовский доверительный интервал 95% [0,342, 0,824]). Была обнаружена существенная гетерогенность (классический τ = 0,076; байесовский τ = 0,195, BF_1 > 1000), при этом байесовский анализ указывает на большую величину вариации. **Вывод:** доступность финансовых услуг оказывает значительное влияние на экономический рост. Однако существенная гетерогенность указывает на контекстно зависимые последствия, требующие разработки индивидуальной политики. Байесовский подход обеспечивает полноту характеристики неопределенности, предлагая более консервативную и реалистичную оценку фактических данных.

Ключевые слова: финансовая доступность; экономический рост; метаанализ; байесовский метаанализ; гетерогенность; экономическое развитие; синтез доказательств; политические последствия; частотная статистика; количественный синтез

Для цитирования: **Afzal M.N.I. Bayesian versus classical perspectives: Does financial inclusion truly drive economic growth? *Review of Business and Economics Studies*. 2025;13(4):95-107. DOI: 10.26794/2308-944X-2025-13-4-95-107**

1. Introduction

Financial inclusion (FI), defined as the widespread availability and utilization of formal financial services, constitutes a fundamental element of contemporary development policy. A vast body of research has explored its potential to drive economic growth (EG), yet the empirical evidence remains fragmented and often contradictory. Studies across different regions and employing varied methodologies have yielded a spectrum of results, from strongly positive to mixed or even negative, creating a puzzle for policymakers seeking to design effective economic strategies. This inconsistency highlights a critical need for a systematic, quantitative synthesis of the existing evidence to clarify the true nature of the FI-EG relationship.

This study addresses this gap by conducting a comprehensive meta-analysis of the FI-EG literature. Our primary objective is to estimate the overall effect size of financial inclusion on economic growth, providing a much-needed consolidated figure. However, we go a step further by employing both classical (frequentist) and Bayesian meta-analytic techniques. This dual-paradigm approach allows for a critical comparison of the results, interpretations, and policy implications derived from each method. By examining how these two dominant statistical frameworks handle issues of uncertainty and heterogeneity, we aim to provide a more nuanced understanding of the FI-EG nexus and offer valuable insights into the practical consequences of methodological choices in evidence synthesis. This research, therefore, not only provides a robust estimate of the FI-EG link but also illuminates the path for future meta-analytic work in economics and beyond.

Despite strong theoretical underpinnings, the empirical literature presents a complex picture. Numerous studies have found a positive FI-EG link in various contexts, including India, Nigeria, and across South Asian Association for Regional Cooperation (SAARC) and Organisation of Islamic Cooperation (OIC) countries [1–4]. However, other research reports mixed or even negative relationships, particularly in regions such as the Middle East and North Africa (MENA) and the Southern African Development Community (SADC), or under specific conditions [5, 6]. Causality also remains debated, with evidence supporting FI driving EG, EG driving FI, or bidirectional links [1, 7, 8]. This heterogeneity in findings underscores the context-specific nature of the FI-EG relationship, which is influenced by factors such as institutional quality, income levels, financial literacy, and the overall development of the financial sector [2, 5, 9].

This inconsistency in empirical results presents a significant research challenge, as policymakers lack a clear and synthesized understanding of the average magnitude and variability of the financial inclusion–economic growth (FI-EG) effect. While literature reviews summarize findings qualitatively, quantitative synthesis through meta-analysis is needed to estimate an overall effect size and quantify the degree of heterogeneity across studies. Furthermore, the meta-analytic literature itself employs different statistical paradigms — primarily classical (frequentist) and Bayesian. These approaches differ in their philosophical underpinnings, estimation methods, and interpretation of results, particularly concerning uncertainty and heterogeneity [10, 11]. A research gap exists in directly comparing these two meta-analytic approaches within the specific, policy-relevant context of the FI-EG nexus.

Therefore, this study aims, firstly, to synthesize the quantitative evidence on the relationship between financial inclusion and economic growth using meta-analysis. Secondly, employ both classical (frequentist) and Bayesian meta-analytic methods to estimate the overall effect size and heterogeneity. Thirdly, critically compare the results, interpretations, and implications derived from the classical and Bayesian approaches in the context of the FI-EG relationship.

This research contributes to the field by providing an updated quantitative synthesis of the FI-EG link and, more importantly, by offering a practical comparison of two major meta-analytic methodologies in applied economics. This comparison highlights how methodological choices can impact the interpretation of synthesized evidence, particularly in relation to the crucial aspect of heterogeneity, providing valuable insights for researchers and policymakers seeking to understand the nuanced relationship between financial inclusion and economic prosperity.

2. Literature review

2.1. Theoretical foundations

The theoretical link between FI and EG is multifaceted. The core argument posits that access to a range of financial services (credit, savings, insurance, payments) is critical for economic activity [1]. By enabling individuals and businesses, particularly micro, small, and medium enterprises (MSMEs) and the poor, to smooth consumption, manage risks, accumulate capital, and undertake productive investments, FI can stimulate economic development [1, 8, 12].

2.1.1. Several specific channels are proposed

The financial institution helps consolidate small savings from the public into productive financial investments, which drives both economic growth and capital development [3, 13]. The availability of credit and financial services enables entrepreneurs to start new businesses as well as support existing businesses at various stages of development and innovation, in line with Schumpeterian theories of economic progress [1, 6, 14]. The implementation of well-functioning financial systems, combined with inclusivity, leads to cost reduction and enhances resource allocation efficiency, thereby enabling better investment planning, which in turn produces higher growth prospects [13]. Households and firms that can obtain insurance coverage alongside multiple savings options manage economic risks better by safeguarding themselves from poverty and investing in reputable but risky enterprises [1, 12]. Conversely, financial exclusion presents significant barriers. Difficulty in accessing credit can stifle MSME growth, limit investment opportunities for the poor, and trap vulnerable populations in poverty cycles, thereby hindering overall economic progress [13, 15].

2.2. Empirical evidence

Empirical investigations into the FI-EG nexus yield diverse findings, reflecting contextual differences and methodological variations.

2.2.1. National level evidence

Several research investigations conducted in individual countries have revealed positive outcomes from their analysis. Research by [1] and [12], among other authors, demonstrates through Autoregressive Distributed Lag (ARDL), error correction model (ECM), Granger causality, and panel data analysis that FI delivers enhanced gross domestic product (GDP) growth during both short-term and long-term periods. The same conclusions emerge in other studies, e.g., [17]. Central to their argument is a shift toward modern financial techniques within the SAARC nations, along with Nigeria. The study [8] provides extensive findings. Further studies [1, 6] show that the per capita GDP of SAARC countries, alongside Iraq, has a parallel relationship with the variable of financial inclusion [1, 2]. The studies produced contradictory findings regarding their results. Multiple studies in the MENA region and in the SADC area have shown that most economic growth patterns exhibit negative long-term relationships among financial development and inclusion elements [5, 6]. Studies have shown negative effects between FI indicators through evaluations of the Nigerian borrower population and Zimbabwean trade-growth relationship [5]. Context-specific interactions exist between financial development and growth, as socio-economic development levels and conditions modify their correlation [6, 8]. Different members of the legislative body express contrasting views about how cause-and-effect connections function. Financial inclusion research generates three distinct models regarding the FI-EG relationship, which assign FI as the driver of EG [1], lead EG to foster FI [7], and demonstrate FI as a parallel force that fosters EG [2, 8].

2.2.2. International level evidence

Global investigations reveal that most findings support a positive relationship between the variables. Various FI indicators (such as bank branches and automated teller machines (ATMs), and depositors) demonstrate positive impacts on EG across large samples of developing countries, OIC nations, and Asian economies, specifically in the long run [2, 4, 5, 6, 9, 16, 17]. The relationship between EG and FI is affected by variations in income level. Studies show that financial inclusion has stronger positive effects in low-income nations with less advanced financial services because such conditions create favorable conditions for FI to generate more benefits [2, 4]. The available literature indicates that governments with robust governance systems can achieve sustainable growth by implementing well-developed, equitable financial institutions [2]. Some evidence suggests that the positive relationship between financial inclusion and economic growth exhibits non-monotonic dynamics, as satisfactory levels of financial inclusion have a heightened impact on economic growth [9].

2.3. Methodological approaches in primary studies

The literature employs diverse econometric techniques, including panel data methods (generalized method of moments (GMM), two-stage least squares (2SLS) regression analysis, panel vector autoregression (PVAR), feasible generalized least squares (FGLS), panel-corrected standard errors (PCSE), fixed effects and dynamic panel threshold) to handle country-specific effects and endogeneity [1, 2, 5, 6, 16, 18], and time-series techniques (ARDL, ECM, Granger causality, VAR) for single-country analyses [1, 7, 8]. Many studies construct composite Financial Inclusion Indices (FIIs), often using principal component analysis (PCA) to weight indicators of access, availability, and usage [1, 4, 9, 19].

2.4. Research gaps and motivation for meta-analysis

Despite extensive research, gaps remain. There is a need for more robust evidence on the macroeconomic impact, understanding precise transmission channels, the role of non-financial factors (social norms, trust, literacy), heterogeneity across contexts, and the impact of digitalization and fintech [2, 3, 5, 7, 20, 21]. The mixed empirical results and context-specificity necessitate a quantitative synthesis via meta-analysis to estimate an average effect size and, crucially, to quantify the extent of inter-study heterogeneity. This study further addresses the methodological gap by comparing classical and Bayesian approaches to this synthesis.

3. Methodology

This study employs a systematic review and meta-analysis approach to explore the relationship between financial inclusion and economic growth at both national and international levels. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, secondary data from peer-reviewed, Scopus-indexed journals were analyzed to assess the impact of financial inclusion on economic growth. The study employed a suitable search strategy and predefined inclusion and exclusion criteria to ensure that only high-quality, relevant research was included in the analysis [22–24].

3.1. Search strategy

On March 23, 2024, searches were performed in electronic databases, including PubMed, Scopus, Web of Science, Google Scholar, and EconLit. The search query was developed using keywords related to financial inclusion and economic growth, national evidence, or international evidence. For financial inclusion, the keyword selection process included (“Financial Inclusion” OR “Banking Access” OR “Credit Access” OR “ATM Booths” OR “Branches of Banks Available for Every 10,000 People” OR “Bank Deposit” OR “Savings Accounts” OR “Remittance”). For economic growth, the keywords used were (“Economic Growth” OR “GDP Growth” OR “Income Distribution” OR “Macroeconomic Stability” OR “Socio-Demographic Development” OR “Political Stability” OR “Employment” OR “Trade Openness” OR “Population Growth”). The relationship term was defined using ("Relation" OR "Impact" OR "Effect" OR "Linkage" OR "Correlation"). To ensure a comprehensive review, the search was further refined using combinations such as ("Financial Inclusion" AND "Economic Growth") AND ("National Evidence" OR "International Evidence"), along with variations like ("Financial Inclusion" OR "Banking Access" OR "Microfinance") AND ("Economic Growth" OR "GDP Growth" OR "Development"). The search also considered economic classifications through ("Financial Inclusion" AND "Economic Growth") AND ("Developing Countries" OR "Developed Countries"), and digital financial services with ("Financial Inclusion" AND "Economic Growth") AND ("Digital Banking" OR "Mobile Money" OR "Microfinance Institutions"). The timeframe was restricted to studies published between 2010 and 2024, using the filter (Year >= 2010 AND Year <= 2024) to ensure contemporary relevance. Additionally, emphasis was placed on empirical analyses by including search queries such as ("Financial Inclusion" AND "Economic Growth") AND ("Causal Relationship" OR "Empirical Analysis" OR "Panel Data Evidence"). These search strategies were systematically applied across multiple databases to ensure a comprehensive collection of studies for review.

3.2. Inclusion and exclusion criteria

This study included peer-reviewed, Scopus-indexed studies that examined the relationship between financial inclusion and economic growth in both developing and developed economies. Specifically, the study considered research focusing on South Asian countries such as Bangladesh and India, as well as studies conducted in African, American, and European nations. To ensure relevance, this study only included studies published between 2010 and 2024. Eligible studies were published in top-tier economic and financial journals, including Elsevier, Taylor and Francis, ResearchGate, and the Journal of Risk and Financial Management. This study included studies that used empirical research methods and provided measurable indicators of financial inclusion, such as bank account ownership, access to credit, mobile banking penetration, microfinance participation, the availability of bank branches, ATM booths, remittance accounts, and savings accounts. Similarly, we selected studies that assessed economic growth using indicators such as GDP growth, income levels, poverty reduction, employment rates, trade openness, income distribution, macroeconomic stability, socio-demographic development, political stability, and population growth. However, this study excluded papers that were non-empirical or lacked data-driven analysis. Studies published in journals other than those indexed in Scopus were also excluded. Since this study focuses on contemporary economic trends, this did not consider studies published before 2010. Additionally, research that failed to report statistical measures such as mean and standard deviation was removed. Lastly, studies that did not explicitly examine the relationship between financial inclusion and economic growth were excluded from inclusion. This selection process ensured that this study is based on high-quality, relevant, and empirical research, providing valuable insights into the impact of financial inclusion on economic growth.

3.3. Study selection and data extraction

The initial searches yielded 550 results, which were from different journals and from different categories. Afterwards, two researchers independently screened the title and the abstract of each study based on the predetermined inclusion and exclusion criteria. The conflicts that were encountered during the title and abstract screening were resolved through discussion between the screeners. Subsequently, 141 studies were selected; however, to satisfy the criteria of publication in top-tier journals and the availability of mean and standard deviation data, some studies were excluded. Eventually, 27 studies were eligible for full-text screening. While conducting the full-text screening, the researchers encountered additional studies in the reference lists that met the inclusion criteria, which were then included in the screening process.

This study employs meta-analysis to synthesize quantitative findings on the FI-EG relationship. We utilize both classical (frequentist) and Bayesian statistical paradigms to provide a comprehensive comparison. The data for the meta-analysis consists of effect sizes (Fisher's z), correlation-based metrics, based on mean and standard deviation extracted from $k = 27$ primary studies investigating the FI-EG link (inferred from $df = 10$ in the PET test). The effect sizes in the meta-analysis were derived from sample size, standard deviation, standard error and mean to correlation coefficients (*r*) first. To ensure normality and stabilize the variance, each correlation coefficient was transformed into Fisher's *z* using the following equation:

$$z = 0.5 * \ln\left(\frac{1+r}{1-r}\right).$$

3.4. Classical (frequentist) meta-analysis
Classical meta-analysis treats parameters as fixed, unknown constants and interprets probability as long-run frequency.

3.4.1. Models

Fixed-Effect Model (FEM) assumes a single population effect size, θ. The observed variance in the FEM arises exclusively from sampling error within individual studies (v_i). The model is defined as:

$$y_i = \theta + \varepsilon_i, where\, \varepsilon_i \sim N(0, v_i).$$

Under the Random-Effects Model (REM), the true effect sizes (θ_i) are assumed to vary, following a normal distribution:

$$\theta_i \sim N(\mu, \tau^2).$$

The observed effect (y_i) is a combination of the true effect and sampling error:

$$y_i = \theta_i + \varepsilon_i\,.$$

Therefore, the observed effects follow a normal distribution with a mean of μ and a variance that includes both within-study variance *(v_i)* and between-study variance (τ^2):

$$y_i \sim N(\mu, v_i + \tau^2).$$

The REM is generally preferred for this type of analysis as it accounts for the expected variability in-country variations in FI measurement data.

3.4.2. Parameter estimation

In the FEM, the overall effect size is calculated as a weighted average of the study effects (y_i), where the weights (w_i) are the inverse of the within-study variance (v_i):

$$w_i = \frac{1}{v_i},$$

$$\hat{\theta}_{FEM} = \frac{\sum w_i y_i}{\sum w_i},$$

$$Var\left(\hat{\theta}_{FEM}\right) = \frac{1}{\sum w_i}.$$

In the REM, the weights account for both within-study variance (v_i) and between-study variance ($\hat{\tau}^2$):

$$w_i = \frac{1}{v_i + \hat{\tau}^2},$$

$$\hat{\mu}_{REM} = \frac{\sum w_i y_i}{\sum w_i},$$

$$Var\left(\hat{\mu}_{REM}\right) = \frac{1}{\sum w_i}.$$

3.4.3. Heterogeneity estimation (τ^2)

Estimating the between-study variance (τ^2) is crucial for the REM. We use the DerSimonian-Laird (DSL) method, a non-iterative method of moments approach based on Cochran's *Q* statistic:

$$Q = \sum w_i \left(y_i - \hat{\theta}_{FEM}\right)^2,$$

$$\hat{\tau}^2_{DSL} = \max\left(0, \frac{Q-(k-1)}{\sum w_i - \frac{\sum w_i^2}{\sum w_i}}\right).$$

3.4.4. Interval estimation

95% confidence intervals (*CIs*) are constructed around the estimated overall effect:

$$CI_{FEM} : \hat{\theta}_{FEM} \pm 1.96 * \sqrt{Var\left(\hat{\theta}_{FEM}\right)},$$

$$CI_{REM} : \hat{\mu}_{REM} \pm 1.96 * \sqrt{Var\left(\hat{\mu}_{REM}\right)}.$$

In a frequentist interpretation, the 95% CI means that if the meta-analysis were repeated many times, the *CI* would contain the true parameter in 95% of the cases. The prediction interval (*PI*) in the REM provides a range for the true effect size in a future study:

$$PI_{REM} : \hat{\mu}_{REM} \pm t_{df} * \sqrt{Var\left(\hat{\mu}_{REM}\right) + \hat{\tau}^2}.$$

3.4.5. Heterogeneity assessment

Cochran's Q tests the null hypothesis of homogeneity (H_0: $\tau^2 = 0$). Under H_0, Q follows a χ^2 distribution with $k - 1$ degrees of freedom. The I^2 statistic quantifies the percentage of total variation across studies that is due to heterogeneity rather than chance:

$$I^2 = \max\left(0, \frac{Q-(k-1)}{Q}\right)*100\% \cdot$$

3.4.6. Publication bias

We use the Precision Effect Test (PET), a form of Egger's regression test, which regresses the study effect sizes (ES_i) on their standard errors (SE_i):

$$ES_i = \beta^0 + \beta^1 * SE_i + \varepsilon_i \, .$$

A significant β_1 coefficient (tested via a t-statistic) suggests funnel plot asymmetry, which can be an indicator of publication bias.

3.5. Bayesian meta-analysis

Bayesian meta-analysis treats all parameters (θ, μ, τ^2) as random variables with probability distributions. Inference updates prior beliefs using observed data (y_i) via Bayes' theorem to obtain posterior distributions.

3.5.1. Models (hierarchical REM)

$$Level\,1(Within-study): y_i \,|\theta_i, v_i \sim N(\theta_i, v_i)\,,$$

$$Level\,2(Between-study): \theta_i \,|\mu, \tau \mathrm{I} \sim N(\mu, \tau \mathrm{I})\,.$$

3.5.2. Priors

Prior distributions must be specified for the hyperparameters μ and τ. For this analysis, we use weakly informative priors. For the overall mean effect (μ), we use a normal distribution with a mean of 0 and a large variance, or a Cauchy distribution:

$$P(\mu) \sim Normal\left(0, \sigma_\mu^2\right) \; or \; P(\mu) \sim Cauchy\left(0, \gamma_\mu\right).$$

For the heterogeneity standard deviation (τ), we use a half-normal or half-Cauchy distribution, as τ must be positive:

$$P(\tau) \sim Half - Normal\left(0, \sigma_\tau^2\right)$$
$$or\; P(\tau) \sim Half - Cauchy\left(0, \gamma_\tau\right) \cdot$$

Based on the comparison table, a half-normal distribution was selected as the prior for τ:

$$P(\tau) \sim Half - Normal + \left(0, \varphi^2\right) \cdot$$

3.5.3. Posterior Estimation

The joint posterior distribution is proportional to the likelihood multiplied by the prior:

$$P\left(y_1, \ldots, y_k\right) \propto Likelihood \times Prior\,.$$

Since closed-form solutions are rare for the REM, Markov Chain Monte Carlo (MCMC) methods, e.g., Gibbs sampling, no-u-turn sampler (NUTS) are used to draw samples from the posterior distributions. Point estimates are summaries of the marginal posterior distributions (e.g., posterior mean or median).

3.5.4. Interval estimation

Bayesian credible intervals (*CrIs*) are derived from the quantiles of the marginal posterior distribution (e.g., the 2.5th and 97.5th percentiles for a 95% *CrI*). A 95% *CrI* for μ, denoted as (L, U), has a direct probabilistic interpretation:

$$P\;(L < \mu < U \,|\, data) = 0.95\,.$$

Uncertainty in the estimation of τ^2 is naturally propagated into the posterior for μ and its *CrI*.

3.5.5. Heterogeneity assessment

The marginal posterior distribution of τ, P (τ | data), directly quantifies the heterogeneity and its uncertainty. Summaries such as the mean, median, and *CrI* can be calculated. Bayes factors (BF_{10}) can be used to compare the evidence for a model with heterogeneity (H_1: $\tau > 0$) versus a model without (H_0: $\tau = 0$). A $BF_{10} > 1$ provides evidence in favor of H_1.

$$BF^{10} = \frac{P\left(H^1\right)}{P\left(H^0\right)} \cdot$$

3.5.6. Software

Bayesian analysis was performed using software R (with packages rjags, rstan, brms) and JASP (open-source statistical software program) employing MCMC methods.

3.6. Methodological comparison framework

We compare the results from classical and Bayesian analyses using two types of approaches to

Table 1
Pooled effect size test

Estimate	Standard Error	*z*	*p*
0.682	0.051	13.393	< .001

Source: Developed by the author.

Table 2
Meta-analytic estimates (including heterogeneity)

Variable	Estimate	95% *CI*		95% *PI*	
		Lower	Upper	Lower	Upper
Effect Size	0.682	0.582	0.782	0.503	0.861
τ	0.076	0.017	0.231		
τ^2	0.006	2.926×10^{-4}	0.053		

Source: Developed by the author.

analyze the overall effect. The width of the respective ranges together with their location determines the interpretation of interval estimates between *CI* vs. *CrI*. The heterogeneity evaluation includes $\hat{\tau}^2$ comparison with $P(\tau^2|\text{data})$ estimation alongside its point evaluation and uncertainty presentation through *CrI* instead of *CI* for τ/τ^2 and final heterogeneity evaluation based on I^2 values and posterior probabilities/BF. Handling of uncertainty (plug-in estimates vs. full propagation). Interpretation of results (long-run frequency vs. probability statements about parameters).

4. Results

4.1. Classical meta-analysis results

The estimated pooled effect size (expressed as Fisher's *z*) calculated under REM comes out to $\hat{\mu} = 0.682$ (*Table 1*). The measurement uncertainty of the estimated mean stands at 0.051. The research results yield a significant statistical value of $z = 13.393$ with a p-value below 0.001 which shows strong evidence contradicting a zero average effect.

Meta-analytic estimates (including heterogeneity).

The REM calculated average effect maintains its original value as $\hat{\mu} = 0.682$ (*Table 2*). The measurement area of the actual average effect size spans (0.582, 0.782) according to a 95% confidence interval (*CI*).

Heterogeneity calculation indicates that the standard deviation of actual effect sizes amounts to $\hat{\tau} = 0.076$. The computed variance of true effect sizes amounts to $\hat{\tau}^2 = 0.006$. The interval estimates show that τ ranges between 0.017 to 0.231 and τ^2 exists between 0.00029 to 0.053. Statistical significance exists because the confidence interval for τ does not contain 0. The wide range of the τ interval indicates that researchers have high levels of uncertainty regarding its actual value. The significant value of τ indicates heterogeneity even though Cochrane Q and I^2 values are not visible in the provided tables. The Prediction Interval demonstrates that the forecast values for the data fall between 0.503 and 0.861 at the 95% confidence level. This broad range of the effect size interval indicates a significant variation in possible results from future studies due to harmful heterogeneity.

Table 3
Test of publication bias (PET)

PET	*t*	df	*p*
Estimate	−1.393	10	0.194

Source: Developed by the author.

The Precision Effect Test yielded a t-statistic of −1.393 with df = 10 (implying $k = 27$ studies). The p-value is 0.194. This result is not statistically significant, suggesting no strong evidence of funnel plot asymmetry of the type detected by this test (i.e., no significant relationship between effect size and standard error). However, the test likely has low power with only 27 studies.

4.2. Bayesian meta-analysis results

Prior distributions (effect size and heterogeneity) are shown on *Fig. 1.*

The prior for the average effect size (μ) appears weakly informative, likely centered at zero with heavy tails (e.g., Cauchy or broad Normal/t). The

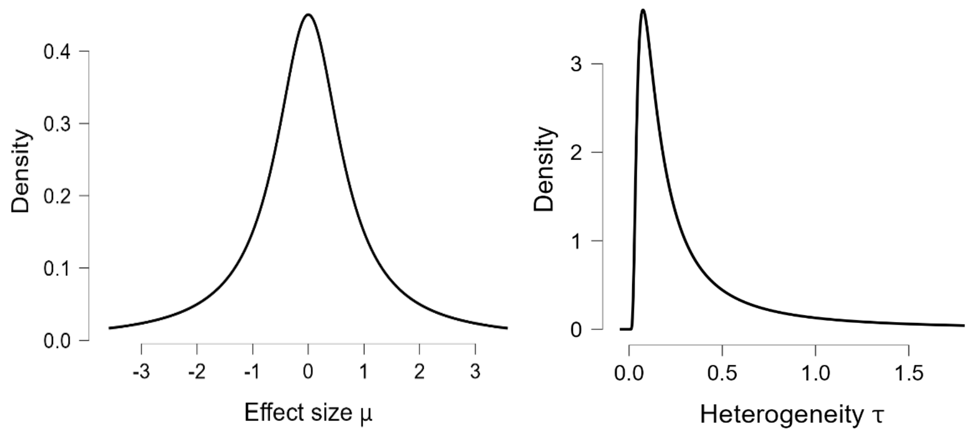

Fig. 1. **Prior distributions**

Source: Developed by the author.

Table 4
Posterior estimates per model (random effects)

Random effects	Mean	SD	Lower	Upper	BF_{10}
μ	0.616	0.121	0.342	0.824	53.813
τ	0.195	0.108	0.058	0.476	48134.155

Source: Developed by the author.

Notes: μ and τ are the group-level effect size and standard deviation, respectively. Posterior estimates per model (random effects). Bayes factor of the random effects H_1 over the fixed effects H_1. 95% credible interval.

prior for the heterogeneity standard deviation (τ) is restricted to be positive, peaks near zero but has a long right tail (e.g., Half-Cauchy or Half-Normal), allowing for potentially large heterogeneity if supported by the data.

4.2.1. Average effect (μ)

The posterior mean estimate is E (μ | data) = 0.616 (*Table 4*). The posterior standard deviation is *SD* (μ | data) = 0.121. The 95% credible interval (*CrI*) is (0.342, 0.824). This interval indicates a 95% probability that the true average effect lies between 0.342 and 0.824, given the data and model. The Bayes Factor comparing H_1: $\mu \neq 0$ vs. H_0: $\mu = 0$ is BF_{10} = 53.813. This provides very strong evidence (BF_{10} >> 10) in favor of a non-zero average effect size.

4.2.2. Heterogeneity (τ)

The posterior mean estimate for the heterogeneity standard deviation is E(τ | data) = 0.195. The posterior standard deviation is *SD* (τ | data) = 0.108. The 95% credible interval (*CrI*) is (0.058, 0.476). This interval clearly excludes zero, providing strong evidence for the presence of heterogeneity. The Bayes factor comparing the random-effects model (H_1: $\tau > 0$) against the fixed-effect model (H_0: $\tau = 0$) is BF_{10} = 48134.155. This extremely large value provides decisive evidence in favor of the random-effects model, i.e., decisive evidence for the presence of heterogeneity.

5. Discussion

This meta-analysis, employing both classical and Bayesian methods, sought to synthesize the evidence on the FI-EG relationship and compare the insights afforded by each statistical approach.

5.1. Synthesis of the FI-EG Relationship

Both methodologies consistently indicate a positive and statistically significant relationship between financial inclusion and economic growth. The classical REM estimate ($\hat{\mu}$ = 0.682) and the Bayesian posterior mean (E(μ|data) = 0.616) are comparable in magnitude, suggesting that, on average, higher financial inclusion is associated with higher economic growth, aligning with the dominant theoretical predictions [1, 14]. The strong statistical significance (Classical $p < 0.001$; Bayesian $BF_{10} = 53.8$) provides robust support for this linkage across the synthesized studies. This meta-analysis uses Fisher's z-transformed correlation coefficients to normalize the effect size distribution and stabilize its variance. This enhances the statistical robustness of the meta-analysis, displaying reported aggregated effect sizes, intervals, and heterogeneity estimates. The magnitude of Fisher's z accurately reflects the positive correlation between financial inclusion and economic growth, validating its reliability across the analyzed studies.

5.2. Comparison of classical and Bayesian results

While converging on the overall positive effect, the two approaches offer different perspectives, particularly regarding uncertainty and heterogeneity

5.2.1. Point estimates

The Bayesian posterior mean for μ (0.616) is slightly lower than the classical REM estimate (0.682). This minor difference could stem from the influence of the weakly informative prior in the Bayesian analysis or differences in how heterogeneity is estimated and incorporated.

5.2.2. Interval estimates

The Bayesian 95% *CrI* for μ (0.342, 0.824) is considerably wider than the classical 95% *CI* (0.582, 0.782). The *CrI* provides a direct probabilistic statement about the parameter's location, which is often considered more intuitive. The wider *CrI* suggests that the Bayesian approach, by fully propagating the uncertainty associated with *all* parameters, including τ, may be capturing a greater degree of uncertainty about the precise magnitude of the average effect compared to the standard classical CI (which often treats $\hat{\tau}^2$ as fixed or uses approximations).

5.2.3. Heterogeneity

This is where the most striking difference emerges. Both methods strongly conclude that significant heterogeneity exists (Classical $\hat{\tau} = 0.076$, 95% *CI* (0.017, 0.231); Bayesian $E(\tau|\text{data}) = 0.195$, 95% *CrI* (0.058, 0.476), $BF_{10} \approx 48134$). However, the Bayesian point estimate of heterogeneity ($\tau \approx 0.195$) is substantially larger than the classical DSL estimate ($\tau \approx 0.076$). The Bayesian 95% *CrI* for τ is also wider than the classical *CI*. This suggests that the true effect of FI on EG likely varies considerably more across different contexts (countries, measures, time periods) than might be inferred from the classical point estimate alone. The extremely high Bayesian BF_{10} provides decisive confirmation of this variability. The classical prediction interval (0.503, 0.861), being much wider than the *CI*, also reflects this heterogeneity practically, indicating substantial expected variation in effects for future studies. The difference in τ estimates could arise from the known potential bias of the DSL estimator versus the MCMC-based Bayesian estimation incorporating a specific prior (half-normal). The Bayesian approach provides the entire posterior distribution for τ, offering a richer understanding of heterogeneity beyond a simple point estimate and *CI*.

5.2.4. Publication bias

The classical PET test did not find significant evidence of publication bias. While reassuring, the low power of such tests with $k = 27$ studies warrants caution. Bayesian methods offer alternative ways to model publication bias (e.g., selection models), although they are not implemented here.

5.2.5. Interpretation

The fundamental difference remains that classical results are interpreted in terms of long-run frequencies of hypothetical repetitions, while Bayesian results offer direct probability statements about parameters conditional on the observed data and chosen model (priors).

5.3. Implications

The consistent finding of a positive average effect reinforces the policy focus on promoting financial inclusion as a strategy for economic growth. For policymakers, this meta-analysis provides a clear, evidence-based mandate to continue and expand efforts to broaden access to financial services. The positive FI-EG link suggests that investments in financial infrastructure, the promotion of digital financial services, and the creation of a regulatory environment that encourages financial innovation are likely to yield significant economic dividends.

However, the significant heterogeneity, particularly emphasized by the Bayesian analysis and the wide classical prediction interval, is critically important. This strongly implies that FI initiatives are not universally applicable. The impact of financial inclusion is highly context-dependent, and policymakers must tailor their interventions to the specific needs and conditions of their economies. For example, in countries with low levels of financial literacy, simply increasing the number of bank accounts may not be sufficient. In such cases, financial inclusion initiatives should be coupled with educational programs to ensure that individuals can make informed financial decisions. Similarly, in economies with weak institutional frameworks, efforts to promote financial inclusion should be accompanied by reforms to strengthen the rule of law and protect property rights.

Methodologically, the comparison between classical and Bayesian approaches offers valuable lessons for researchers. While both methods can lead to similar conclusions about the direction of an effect, the Bayesian framework provides a more nuanced and arguably more realistic assessment of uncertainty and heterogeneity. The ability of Bayesian methods to incorporate prior information and provide direct probabilistic statements about parameters makes them a powerful tool for evidence synthesis, particularly in fields like economics, where context is crucial. Researchers should consider the strengths and weaknesses of both approaches and select the method that best suits their research question and the nature of their data.

In conclusion, this study provides a robust and nuanced understanding of the FI-EG relationship. It confirms the positive role of financial inclusion in driving economic growth, while also highlighting the critical importance of context and the practical implications of methodological choices in evidence synthesis. For policymakers, the message is clear: promoting financial inclusion is a worthwhile endeavor, but it must be done thoughtfully and with a deep understanding of the local context. For researchers, this study provides a practical guide to the application and interpretation of classical and Bayesian meta-analytic techniques, paving the way for more sophisticated and insightful evidence synthesis in the future.

6. Conclusion

This study synthesized the quantitative evidence on the relationship between financial inclusion and economic growth using both classical and Bayesian meta-analysis. Both approaches robustly support a positive and statistically significant average association, confirming the theoretical importance of FI for EG. Furthermore, both methods provide strong evidence for the existence of significant heterogeneity in the true effect sizes (expressed as Fisher's z) across studies.

The comparative analysis revealed nuances: while the direction and statistical significance of the average effect were consistent, the Bayesian analysis yielded a slightly lower point estimate, a wider credible interval for the average effect, and a substantially larger estimate for the magnitude of heterogeneity (τ) compared to the classical DerSimonian-Laird approach. The Bayesian framework, through its full propagation of uncertainty and provision of posterior distributions, offered a richer characterization of the variability inherent in the FI-EG relationship.

The presence of substantial heterogeneity underscores the importance of context in mediating the impact of FI policies. The findings highlight that while promoting FI is generally beneficial for growth, the specific outcomes can vary significantly, necessitating tailored policy design. Methodologically, the study demonstrates that the choice between classical and Bayesian meta-analysis can influence the quantification of uncertainty and heterogeneity, with Bayesian methods potentially offering a more comprehensive picture, particularly regarding the variability of effects across diverse settings.

6.1. Contribution

The study presents modern quantitative information on the total effect size of the FI-EG relationship. The approach explicitly demonstrates the considerable diversity present throughout the analyzed studies. The primary value of this research lies in the applied scientific comparison between classical and Bayesian meta-analysis in this relevant economic setting. The study demonstrates the analytical methods used for different estimation and interpretation processes, specifically addressing heterogeneity and uncertainty, and provides useful information for researchers analyzing and interpreting meta-analytic evidence in economic settings and related disciplines.

6.2. Limitations and future research

This study has limitations. The meta-analysis was based on only 27 primary studies, limiting statistical power (especially for publication bias tests) and the ability to explore sources of heterogeneity robustly. The specific effect size metric used in the primary studies was inferred rather than explicitly stated. The quality and potential biases within the primary studies inevitably carry over to the meta-analysis. We did not conduct meta-regression to investigate specific moderators (e.g., income level, region, and FI measurement) that could explain the observed heterogeneity, which constitutes a crucial next step. Sensitivity analysis regarding prior choices in the Bayesian framework could also be explored further.

Future research should aim to include a larger number of studies, allowing for more powerful analyses and robust investigation of heterogeneity sources through meta-regression using both classical and Bayesian techniques. Examining different dimensions of FI (access, usage, quality) and EG (e.g., poverty reduction, inequality) within a meta-analytic framework would also be valuable. Incorporating more advanced Bayesian models, potentially addressing publication bias, or utilizing network meta-analysis when comparing different FI interventions could provide deeper insights.

During the preparation of this work, the author used Google AI Studio in order to improve the grammar and language of the manuscript. After using this tool (service), the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

REFERENCES

1. Ali M., Hashmi S.H., Nazir M.R., Bilal A., Nazir M.I. Does financial inclusion enhance economic growth? Empirical evidence from the IsDB member countries. *International Journal of Finance and Economics*. 2021;26(4):5235–5258. DOI: 10.1002/ijfe.2063
2. Alkhafagy T., Abd M., Nsaif A.D., Alasadi S.R., Al-Muttar M.Y.O. Does financial development and financial inclusion matter for economic growth? Evidence from Iraq. *Cuadernos de Economía*. 2023;46(131). DOI: 10.32833/cude.v46i131.419
3. Ashenafi Biru A., Molla A., Ferraro S., Navon Y. The impact of financial inclusion initiatives: Evidence from meta-analysis. *Journal of International Development*. 2024;36(8):2926–2958. DOI: 10.1002/jid.3943
4. Asuming P.O., Osei-Agyei L.G., Mohammed J.I. Financial inclusion in Sub-Saharan Africa: Recent trends and determinants. *Journal of African Business*. 2019;20(1):112–134. DOI: 10.1080/15228916.2018.1484209
5. Azmeh C., Al-Raeei M. Exploring the dual relationship between fintech and financial inclusion in developing countries and their impact on economic growth: Supplement or substitute? *PLoS One*. 2024;19(12): e0315174. DOI: 10.1371/journal.pone.0315174
6. Banik S., Padhan P.C. Financial inclusion and economic development in the SAARC region. *Journal of Economic and Administrative Sciences*. 2023;40(2):263–281. DOI: 10.1108/JEAS-03–2023–0075
7. Cabeza-García L., Del Brio E.B., Rueda C. The effect of financial development on renewable energy consumption: A panel data analysis. *Energy*. 2019;170:173–181. DOI: 10.1016/j.energy.2018.12.125
8. Chinoda T. The impact of financial inclusion on economic growth in Zimbabwe. *Cogent Economics and Finance*. 2020;8(1):1845310. DOI: 10.1080/23322039.2020.1845310
9. Zehri C., Mosbah E., Kadja A., Inaam Z., Sekrafi H. exploring the nexus of decent work, financial inclusion, and economic growth: A study aligned with SDG 8. *Sustainable Futures*. 2024;7:100213. DOI: 10.1016/j.sftr.2024.100213
10. Domeher D., Konadu-Yiadom E., Aawaar G. Financial innovations and economic growth: Does financial inclusion play a mediating role? *Cogent Business and Management*. 2022;9(1):2115651. DOI: 10.1080/23311975.2022.2115651
11. Grohmann A., Klühs T., Menkhoff L. Does financial literacy improve financial inclusion? Cross country evidence. *World Development*. 2018;111:84–96. DOI: 10.1016/j.worlddev.2018.06.020
12. Hussain S., Rehman A.U., Ullah S., Waheed A., Hassan S. Financial inclusion and economic growth: Comparative panel evidence from developed and developing Asian countries. *SAGE Open*. 2024;14(1). DOI: 10.1177/21582440241226740

13. Ioan B., Kumaran R.M., Larissa B., Anca N., Lucian G., Gheorghe F., Horia T., Ioan B., Mircea-Iosif R. A panel data analysis on sustainable economic growth in India, Brazil, and Romania. *Journal of Risk and Financial Management*. 2020;13(8):170. DOI: 10.3390/jrfm13080170
14. Kabakova O., Plaksenkov E. Analysis of factors affecting financial inclusion: Ecosystem view. *Journal of Business Research*. 2018;89:198–205. DOI: 10.1016/j.jbusres.2018.01.066
15. Kimmitt J., Muñoz P. Entrepreneurship and financial inclusion through the lens of instrumental freedoms. *International Small Business Journal*. 2017;35(7):803–828. DOI: 10.1177/0266242617696354
16. Koomson I., Villano R.A., Hadley D. Effect of financial inclusion on poverty and vulnerability to poverty: Evidence using a multidimensional measure of financial inclusion. *Social Indicators Research*. 2020;149:613–639. DOI: 10.1007/s11205–019–02263–0
17. Le T.H., Chuc A.T., Taghizadeh-Hesary F. Financial inclusion and its impact on financial efficiency and sustainability: Empirical evidence from Asia. *Borsa Istanbul Review*. 2019;19(4):310–322. DOI: 10.1016/j.bir.2019.07.002
18. N'dri L.M., Kakinaka M. Financial inclusion, mobile money, and individual welfare: The case of Burkina Faso. *Telecommunications Policy*. 2020;44(3):101926. DOI: 10.1016/j.telpol.2020.101926
19. Nizam R., Karim Z.A., Rahman A.A., Sarmidi T. Financial inclusiveness and economic growth: new evidence using a threshold regression analysis. *Economic Research-Ekonomska Istraživanja*. 2020;33(1):1465–1484. DOI: 10.1080/1331677X.2020.1748508
20. Ohlan R. The relationship between tourism, financial development and economic growth in India. *Future Business Journal*. 2017;3(1):9–22. DOI: 10.1016/j.fbj.2017.01.003
21. Okello Candiya Bongomin G., Mpeera Ntayi J., Munene J.C., Malinga Akol C. Financial intermediation and financial inclusion of poor households: Mediating role of social networks in rural Uganda. *Cogent Economics and Finance*. 2017;5(1):1362184. DOI: 10.1080/23322039.2017.1362184
22. Ouechtati I. The contribution of financial inclusion in reducing poverty and income inequality in developing countries. *Asian Economic and Financial Review*. 2020;10(9):1051–1061. DOI: 10.18488/journal.aefr.2020.109.1051.1061
23. Ramzan M., Amin M., Abbas M. How does corporate social responsibility affect financial performance, financial stability, and financial inclusion in the banking sector? Evidence from Pakistan. *Research in International Business and Finance*. 2021;55:101314. DOI: 10.1016/j.ribaf.2020.101314
24. Shahbaz M., Sbia R., Hamdi H., Ozturk I. Economic growth, electricity consumption, urbanization, and environmental degradation relationship in the United Arab Emirates. *Ecological Indicators*. 2014;45:622–631. DOI: 10.1016/j.ecolind.2014.05.022

ABOUT THE AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

Munshi Naser Ibne Afzal — PhD in Economics, Professor of Economics, Business and Law, University of Southern Queensland, Sylhet, Bangladesh; Hamdan Bin Mohammed Smart University (HBMSU), Dubai, United Arab Emirates (UAE)
Мунши Насер Ибне Афзал — PhD в области экономики, профессор экономики, бизнеса и права, Университет Южного Квинсленда, Силхет, Бангладеш; Университет Хамдана Бин Мохаммеда Смарт (HBMSU), Дубай, Объединенные Арабские Эмираты (ОАЭ)
https://orcid.org/0000-0002-6351-4856
munshinaser-eco@sust.edu

Conflicts of Interest Statement: The author has no conflicts of interest to declare.
The article was submitted on 30.03.2025; revised on 20.11.2025 and accepted for publication on 30.11.2025.
The author read and approved the final version of the manuscript.