
Research article

Financial development and the circular economy: Evidence across levels of economic development

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Abstract: The circular economy has become increasingly important as countries seek to reduce resource dependence, improve energy efficiency, and decouple economic activity from environmental pressure. However, macro-level circular economy measurement remains fragmented, while the relationship between financial development and circular transition may differ substantially across levels of economic development. In this study, we constructed a macro-level circular economy index for 109 countries over the period 2002–2024, comprising 30 developed and 79 developing economies. Principal component analysis combined four dimensions: carbon efficiency, energy efficiency, energy transition, and material pressure. Bayesian regression was then used to examine the relationship between financial development and circular economy performance under six institutional specifications. The results revealed a substantial development gap: The mean circular economy index was 0.864 for developed countries and 0.413 for developing countries. In developed economies, the posterior coefficient of financial development ranged from 0.0017 to 0.0023, with $P(\beta > 0) = 1.0000$ across all six specifications. The corresponding approximate 95% credible intervals remained strictly positive, ranging from approximately [0.0013, 0.0021] to [0.0021, 0.0025], providing strong evidence of a stable positive relationship. In developing economies, the coefficients were substantially smaller and heterogeneous, ranging from -0.0005 to 0.0001 . Most posterior intervals overlapped zero, while the political-stability specification produced a negative coefficient of -0.0005 , with $P(\beta < 0) = 1.0000$ and an approximate 95% credible interval of $[-0.0007, -0.0003]$. These findings indicated that greater financial depth is

consistently associated with stronger circular economy performance in developed economies but does not generate the same outcome in developing countries. The results highlight the importance of directing financial resources toward clean technology, renewable energy, resource efficiency, recycling, and other circular activities rather than relying on credit expansion alone.

Keywords: circular economy; financial development; principal component analysis; Bayesian regression; developed and developing countries

JEL Codes: G21, O13, Q01, Q56

Abbreviations: CE: Circular economy; FD: Financial development; IQ: Institutional quality; PCA: Principal component analysis; KMO: Kaiser–Meyer–Olkin; CAE: Carbon efficiency; EE: Energy efficiency; ET: Energy transition; RE: Material pressure; CC: Control of corruption; GE: Government effectiveness; PS: Political stability; RL: Rule of law; RQ: Regulatory quality; VA: Voice and accountability; GDPG: GDP per capita growth; FDI: Foreign direct investment; INF: Inflation; UNE: Unemployment; UR: Urbanization; INT: Internet use; WDI: World development indicators; WGI: Worldwide governance indicators; FEM: Fixed effects model; REM: Random effects model; OLS: Ordinary least squares; MCMC: Markov chain monte carlo; DWH: Durbin–Wu–Hausman; MF: Material flow; GFC: Global Financial Crisis

1. Introduction

The circular economy has become an important research direction in sustainable development. Its central concern is to change the way economies use resources. Instead of extracting, producing, consuming, and discarding, the circular economy seeks to keep materials, energy, and products within the economic system for a longer period. This approach reduces waste, lowers pressure on natural resources, and limits the volume of waste generated. It differs fundamentally from the linear economy, which relies heavily on primary resource extraction and end of life waste treatment. As climate change, resource depletion, and waste pollution become more severe, the limits of the linear model become increasingly visible, not only environmentally but also in terms of long run economic efficiency (Chowdhury et al., 2026).

Global evidence shows that the gap between circular economy goals and the current level of circularity remains large. Circle Economy (2024) reports that the world economy consumes more than 100 billion tons of materials each year, while only about 6.9 percent of materials are cycled back into production. WRI (2025) also argues that the global average material footprint remains far above a long run sustainable level. These facts imply that economic growth is closely tied to primary resource extraction, material consumption, and waste generation. The circular transition is therefore not merely a recycling issue; it is a question of restructuring the growth model.

A fundamental difficulty in circular economy research concerns measurement. A country with a high recycling rate is not necessarily highly circular if its material consumption and carbon emissions

remain high. Conversely, a country with low material consumption per capita does not necessarily have a strong circular economy, because low consumption may reflect low income, a small industrial base, or limited production capacity. The use of a single indicator can therefore lead to misleading assessments, especially when developed and developing countries are compared.

Circular economy indicators remain fragmented across levels of analysis. At the micro level, many researchers focus on products, firms, dismantling, recycling, or material value retention (Das et al., 2000; Lee et al., 2014; Nelen et al., 2014; Conca et al., 2026). At the meso level, researchers often examine eco industrial parks, territories, or industrial symbiosis (Park and Behera, 2014; Huysman et al., 2015; Scheepens et al., 2016). At the macro level, studies have begun to construct national indicators, but most remain constrained by regional scope, data availability, or indicator selection (Claudio Quiroga and Poza, 2024; Drofenik et al., 2025; Emami et al., 2025; Hoang et al., 2026). This gap weakens the basis for cross country comparison.

In this article, we argue that a macro level circular economy measure should capture several dimensions of transition at the same time, rather than focusing only on recycling or end of life waste management. The proposed dimensions are carbon efficiency, energy efficiency, energy transition, and material pressure: Carbon efficiency reflects the ability to generate economic value with lower emissions. Energy efficiency reflects the productivity of energy use. Energy transition captures the shift from fossil fuels toward renewable energy. Material pressure reflects the degree to which an economy depends on material inputs and primary resources. When combined using principal component analysis, these dimensions provide a composite index suitable for international comparison.

The second gap concerns the role of financial development. The finance and growth literature has long emphasized the role of the financial system in mobilizing savings, allocating capital, monitoring investment, managing risk, and promoting technological innovation (Schumpeter, 1911; King and Levine, 1993; Levine, 1997; Beck et al., 2000). In the circular economy context, this role is especially relevant because circular projects often require large capital commitments, long payback periods, and higher uncertainty than conventional production projects. Investment in clean technology, circular design, renewable energy, recycling, and remanufacturing requires support from bank credit, capital markets, and sustainable finance instruments (Ellen MacArthur Foundation, 2015).

However, the effect of financial development on the circular economy should not be expected to be uniform across levels of development. Developed economies generally have deeper financial systems, stronger technological capacity, and more mature environmental infrastructure, which can improve the ability of financial institutions and capital markets to support long horizon investments in clean technology, renewable energy, recycling, and resource efficient production. In contrast, developing economies often face tighter financing constraints, more limited green investment capacity, and production structures that remain more dependent on resource and energy intensive activities. Under these conditions, an expansion of credit may finance conventional production and consumption rather than circular transformation. This distinction is important because the same increase in financial depth can generate different circular economy outcomes depending on where capital is allocated and on the structural capacity of an economy to absorb finance into circular activities. Chen et al. (2026) showed that domestic credit to the private sector is positively associated with municipal waste per capita in 28 European countries. Fang et al. (2024) noted that investment devoted to the circular economy remains limited compared with broader sustainable investment. The research question is

therefore not simply whether finance develops, but whether financial development is translated into investment that supports circularity, and whether this translation differs systematically between developed and developing countries.

Based on these gaps, we have two objectives: The first is to construct a macro level composite circular economy measure that can be compared across countries. The second is to examine whether financial development affects circular economy performance differently in developed and developing countries after controlling for basic macroeconomic characteristics. We therefore address three related research questions: How can the circular economy at the national level be measured in a way that reflects its multidimensional nature? How does financial development affect the circular economy index? Does the magnitude or direction of this effect differ between developed and developing economies?

The novelty of the article lies in bringing together three elements that are usually examined separately. First, we move beyond single indicators by constructing a national circular economy index that jointly captures carbon efficiency, energy efficiency, energy transition, and material pressure, enabling a broader comparison across 109 countries. Second, rather than assuming that the finance circular economy relationship is homogeneous, we explicitly compare developed and developing countries, where differences in financial depth, technological capacity, and production structure may condition how credit is translated into circular outcomes. Third, we link financial intermediation theory to this comparative setting and combine PCA-based index construction with Bayesian regression, enabling the analysis to account for substantial cross-country heterogeneity and to evaluate the probability, direction, and stability of the financial development effect across the two country groups. In this way, the study contributes not only a new macro level measure of circular economy performance but also a clearer explanation of when financial development is more likely to support circular transition.

The remainder of the article is organized as follows: In Section 2, we present the theoretical background and literature review. In Section 3, we describe the research design, data, variables, and analytical methods. In Section 4, we report the empirical results. In Section 5, we conclude and provide policy implications.

2. Theoretical background and literature review

2.1. The concept of circular economy and measurement logic

The circular economy is understood as an economic system that aims to maintain the value of products, materials, and resources in the economy for as long as possible while reducing waste and limiting the extraction of primary resources (Ellen MacArthur Foundation, 2015; Lieder and Rashid, 2016). This understanding is broader than waste management. It covers product design, material selection, production, consumption, reuse, repair, remanufacturing, recycling, and value recovery. The circular economy should therefore be seen as an economic system rather than a set of isolated environmental activities (Xie et al., 2020; Lieder and Rashid, 2016).

A major difficulty in circular economy research is the absence of a unified definition. Kirchherr et al. (2017), Murray et al. (2017), and Ghisellini et al. (2020) showed that the circular economy is interpreted differently depending on the level of analysis and policy objective. This inconsistency affects measurement, indicator choice, and empirical conclusions. If circular economy is understood

mainly as recycling, researchers prioritize recycling indicators. If it is understood as resource efficiency, researchers prioritize resource productivity and material intensity. If it is understood as system transition, a more comprehensive measure is needed.

The R framework is a common way to explain the operational logic of the circular economy. The early 3R framework of Reduce, Reuse, and Recycle emphasized reducing resource use, reusing products, and recycling materials (Yong, 2007; Zhijun and Nailing, 2007; Jiao and Boons, 2017). Later, Recover was added to reflect material and energy recovery (European Commission, 2008; Allwood et al., 2011). Researchers extend this logic to the 9R framework, emphasizing a hierarchy of value retention from refuse, rethink, reduce, reuse, repair, refurbish, remanufacture, repurpose, and recycle to energy recovery (Potting et al., 2017; Munoz, 2024; Nazir and Doni, 2024; Toboso-Chavero et al., 2025). The key point is that circularity should not begin at the end of a product life cycle, but from design and the reduction of material demand at the outset.

From a macro measurement perspective, the R framework provides a theoretical foundation but cannot directly generate a national index unless it is translated into internationally comparable indicators. Firm or product level indicators are difficult to apply to a multi country sample because comparable data are scarce. We therefore approach the circular economy through observable national outcomes: carbon emissions per unit of GDP, energy productivity, the share of renewable energy in primary energy consumption, and domestic material consumption per unit of GDP (Li et al., 2019). This approach does not measure every aspect of circularity, but it is more suitable for macro comparison and for testing the role of financial development.

2.2. Approaches to measuring the circular economy

Circular economy measurement can be grouped into three levels: micro, meso, and macro. At the micro level, researchers often focus on products or firms. Das et al. (2000) proposed a disassembly effort index for measuring the effort required to dismantle products after use. Lee et al. (2014) developed an end-of-life index for electrical equipment. Nelen et al. (2014) built a recycling indicator set for LCD televisions in Europe. Van Schaik and Reuter (2016) developed recycling indices for LED and LCD systems. These studies clarify material value retention at the product level, but they are difficult to generalize into national indicators.

At the firm level, Li and Su (2012) constructed a circular economy indicator system for chemical enterprises in China; Evans and Bocken (2013) proposed a qualitative assessment toolkit; Di Maio and Rem (2015) developed an index based on material value in the context of automobile recycling in Europe; Do Minh and Nguyen (2022) applied the Material Circularity Indicator to packaging firms in Vietnam; and Conca et al. (2026) measured circular economy practices at the global firm level using Refinitiv data. These studies are close to corporate practice, but firm data do not fully reflect material, energy, and emissions structures at the economy wide level.

At the meso level, researchers often analyze industrial parks, regions, or production ecosystems. Qing et al. (2011) constructed a provincial indicator system for Shaanxi; Geng et al. (2012) developed a multi scale measure for 30 Chinese provinces; Park and Behera (2014) proposed eco efficiency indicators for the Ulsan eco industrial park; Huysman et al. (2015) built a recycling benefit rate for Flanders; and

Scheepens et al. (2016) applied an eco-cost value ratio in sustainable tourism in the Netherlands. These studies highlight interactions among actors in a system, but they remain context dependent.

At the macro level, researchers have moved toward national or regional indices. Claudio Quiroga and Poza (2024) constructed a multidimensional circular economy index for European countries based on the European Commission monitoring framework. Drofenik et al. (2025) applied a national circularity index for Slovenia. Emami et al. (2025) measured the circular economy of ASEAN using material flow accounting. Hoang et al. (2026) measured the circular economy at the provincial level in Vietnam using solid waste treatment, collection, and sorting indicators. Dat et al. (2025) examined the factors shaping the circular economy in Vietnam and showed that Reduce, Reuse, Recycle, Rethink, and Refuse contribute differently to circular economy development, with Reduce emerging as the most influential factor. Similarly, Streimikis et al. (2024) assessed circular economy development in the Visegrad countries using a multidimensional indicator framework and MCDM-based ranking, demonstrating considerable variation in circular economy performance across countries. These studies show the growing need for macro measurement, but also reveal dependence on regional data, context-specific indicators, and methodological choices that limit broader cross-country comparability.

Two observations follow from the literature: First, the circular economy is multidimensional, while many measures capture only a single dimension. Second, macro level studies lack a measure that is simple enough for large samples yet broad enough to reflect the nature of circular transition. We therefore propose a circular economy index based on four internationally observable pillars: carbon efficiency, energy efficiency, energy transition, and material pressure.

2.3. Financial development and the circular economy

Financial development generally refers to the expansion and improvement of the financial system in mobilizing savings, allocating capital, monitoring investment, managing risk, and supporting economic transactions. Financial intermediation theory argues that financial systems reduce information asymmetry, improve project selection, and allocate capital to more productive sectors (Levine, 1997; Beck et al., 2000). King and Levine (1993) showed that financial development indicators are closely related to GDP per capita growth, capital accumulation, and capital efficiency. This argument can be extended to the circular economy because the circular transition also requires capital, technological innovation, and a willingness to bear long term risk.

Finance can affect the circular economy through three potential channels. The first is capital mobilization for long payback investments such as clean technology, recycling infrastructure, renewable energy, material recovery systems, and production process innovation. The second is capital allocation, through which the financial system can prioritize resource saving projects, low emission production, and circular business models. The third is risk management, because financial institutions can help firms manage technological, market, and transition risks during production transformation (Ellen MacArthur Foundation, 2015; Chowdhury et al., 2026).

Evidence suggests that green finance, sustainable finance, green bonds, microfinance, and impact investment can support the circular transition by directing capital toward resource saving and waste reducing activities (Desalegn and Tangl, 2022; Chen and Chen, 2025; Munonye and Munonye, 2025). Evidence also suggests that the contribution of financial development to sustainable economic

outcomes depends on broader institutional and environmental conditions (Krasnoselskaya and Timiryanova, 2023; Cai et al., 2025). Rani et al. (2023) further showed that the relationship between financial development and environmental degradation varies across environmental conditions, suggesting that greater financial depth does not necessarily translate into better environmental outcomes. Moreover, Rani et al. (2025) showed that green investment, green electricity, and green technological innovation can support environmental improvement, while the environmental consequences of financial development depend on how financial resources are allocated. Related evidence also shows that financial inclusion and market-based environmental instruments can influence environmental outcomes and support the expansion of renewable energy, highlighting the broader role of financial mechanisms in sustainable transition (Bajwa et al., 2025; Cheng and Jiang, 2024). However, this evidence is insufficient to conclude that financial development in general always promotes the circular economy.

The dual nature of financial development should therefore be emphasized. On the one hand, finance can help firms overcome capital barriers and invest in circular technologies. On the other hand, when capital flows lack environmental direction, finance can increase material consumption, expand linear production, and generate more waste. Chen et al. (2026) showed that domestic credit to the private sector can be positively associated with municipal waste per capita in European countries. Thus, the scale of finance does not always equal the quality of transition. The empirical question must be stated cautiously: How does financial development affect a composite circular economy index when circularity is measured through multiple dimensions rather than a single indicator?

The literature reveals three major gaps. The first is measurement. Many researchers use single indicators to represent the circular economy, although circularity is a multidimensional process. This weakens cross country comparison and can distort empirical tests of its determinants.

The second gap is the level of analysis. Evidence often focuses on products, firms, or industrial parks. These studies explain micro mechanisms, but they are not sufficient to explain why circular economy performance differs across countries. A macro level measure is needed when the aim is to analyze determinants such as financial development, economic growth, inflation, unemployment, urbanization, or digital infrastructure.

The third gap is that the relationship between financial development and the circular economy remains inconclusive. Finance can support circular transition, but it can also increase resource pressure if capital serves linear production expansion. A direct empirical model linking financial development to a composite circular economy index is therefore needed.

3. Materials and methods

3.1. Research design

In this study, we use a quantitative approach with two major steps. The first step constructs a macro level circular economy index using principal component analysis. The second step examines the impact of financial development on the circular economy index using panel data regression. This design is consistent with our two objectives of the paper: Measuring the circular economy and analyzing the role of financial development in the circular transition.

3.2. *Data and sample*

We use a panel dataset of 109 countries over the period 2002 to 2024. The sample includes 30 developed countries and 79 developing countries, classified according to the International Monetary Fund. The period is chosen based on the availability, completeness, and comparability of data on carbon emissions, energy, material consumption, financial development, and macroeconomic control variables.

Data are collected from internationally comparable sources, including the World Bank World Development Indicators, Our World in Data, and the Global Material Flows Database. The use of international data reduces bias from differences in national statistical systems and increases the replicability of the study. Missing observations are handled transparently by retaining countries with sufficient data to construct the index and estimate the model over the research period.

3.3. *Variables and measurement*

The dependent variable is the macro level circular economy index. It is constructed from four component indicators: carbon efficiency, energy efficiency, energy transition, and material pressure. The selection of these four indicators reflects conceptual relevance and the need for consistent cross-country measurement over the long period covered by the study. Circular economy performance is inherently multidimensional, and no single indicator can capture all aspects of circularity. Moraga et al. (2019), for example, showed that circular economy indicators measure different strategies and system boundaries and argued that a set of complementary indicators is more appropriate than relying on a single measure. Similarly, Saidani et al. (2019) identified substantial heterogeneity among circular economy indicators in terms of scale, circularity loops, performance dimensions, and intended use.

The four indicators used in this study are therefore selected to represent four broad macroeconomic outcomes of circular transition. Carbon efficiency captures the ability of an economy to generate economic value with lower emissions (Li et al., 2019; Ferrari et al., 2025); energy efficiency reflects the productivity of energy use; energy transition represents the movement from fossil-based energy systems toward renewable energy; and material pressure captures the amount of domestic material consumption required to generate economic output. This structure is also consistent with the broader direction of circular economy monitoring frameworks, which increasingly combine resource productivity, material use, and environmental pressures rather than treating recycling as the sole measure of circularity. The revised EU Circular Economy Monitoring Framework, for instance, includes resource productivity, material footprint, greenhouse gas emissions, waste management, and secondary raw-material indicators as complementary dimensions.

Recycling rates, waste generation, and resource recovery are considered conceptually relevant but are not included in the composite index for two reasons. First, these indicators capture important but relatively downstream dimensions of circularity. A high recycling rate does not necessarily indicate a highly circular economy if material consumption, energy dependence, and emissions remain high. Moraga et al. (2019) similarly cautioned that many circular economy indicators are concentrated on material preservation and recycling and therefore capture only part of the circular transition. Second, internationally harmonized annual data on recycling, waste generation, and secondary material use are considerably more limited across developing economies and over the 2002–2024 period. Several such

indicators are well developed within the European statistical system, but their consistent coverage is substantially weaker for a global sample of 109 countries. By contrast, domestic material consumption is a standardized material-flow accounting indicator that measures the quantity of materials directly used in an economy and is suitable for cross-country macroeconomic comparison.

The main independent variable is financial development, measured by domestic credit to the private sector as a share of GDP. This is a common measure in financial development research because it reflects the extent to which the financial system supplies capital to the private sector. In the circular economy context, private credit can support investment in clean technologies, renewable energy, production innovation, and circular business models. However, it may also reflect credit expansion into resource intensive sectors, so its direction of impact must be tested empirically.

Control variables include economic growth, inflation, unemployment, urbanization, and the share of Internet users. These variables control for macroeconomic characteristics that may affect the circular economy: Economic growth may increase the capacity to invest in clean technology but can also raise material consumption. Inflation reflects macroeconomic instability and may reduce long term investment. Unemployment reflects labor market conditions and production structure. Urbanization increases waste pressure but can also support centralized recycling and resource management infrastructure. Internet use captures digital capacity, which can support monitoring, production optimization, and circular business models.

Table 1. Proposed indicators for constructing the circular economy index.

Measurement pillar	Symbol	Measurement	Expected direction	Economic meaning	References
Carbon efficiency	CAE	CO2 emissions per unit of GDP, kg CO2 per GDP based on 2021 PPP	Negative; lower values are better	Reflects the ability to create economic value with lower emissions	Circle Economy (2024); WRI (2025)
Energy efficiency	EE	GDP based on 2021 PPP per unit of energy use	Positive; higher values are better	Reflects energy productivity and the degree of decoupling growth from energy consumption	Geng et al. (2012); Emami et al. (2025)
Energy transition	ET	Share of renewable energy in total primary energy consumption	Positive; higher values are better	Reflects the shift away from fossil energy	Ellen MacArthur Foundation (2015)
Material pressure	RE	Domestic material consumption per GDP	Negative; lower values are better	Reflects dependence on material inputs and primary resources	Mayer et al. (2019); Haas et al. (2020); Emami et al. (2025)

Source: Authors' compilation.

3.4. Constructing the circular economy index using principal component analysis

Principal component analysis (PCA) is used to construct the circular economy index because it enables several correlated indicators to be combined into a composite measure. PCA does not assign weights subjectively. Instead, it derives weights from the variance structure of the data. This approach is appropriate for building a measure that is internationally comparable and less dependent on arbitrary weighting (Abdi and Williams, 2010).

The index construction follows four steps: First, component indicators are selected based on theory and data availability. Second, the expected direction of each variable is harmonized. For positive indicators, higher values reflect better circular economy performance. For negative indicators, such as carbon intensity and material pressure, the variables are reversed so that higher values reflect better performance. Third, data are standardized to place all variables on the same scale. Fourth, PCA is applied to extract the principal component that represents the degree of circular economy transition. The final index is normalized on a 0 to 1 scale to facilitate interpretation and comparison.

Before applying PCA, the suitability of the data is assessed using the correlation matrix, the Kaiser Meyer Olkin statistic, and Bartlett's test. The correlation matrix indicates whether the indicators reflect a common phenomenon. The KMO statistic assesses sampling adequacy for factor analysis, while Bartlett's test evaluates the null hypothesis that the correlation matrix is an identity matrix. If the minimum conditions are not satisfied, the choice of indicators or standardization procedure should be reconsidered.

3.5. Empirical model

After constructing the circular economy (CE) index, we examine the relationship between financial development and circular economy performance using a panel-data framework. The empirical specification treats the CE index as the dependent variable, financial development (FD) as the main explanatory variable, institutional quality (IQ) as an institutional control, and a set of macroeconomic controls. Country-specific and time-specific effects are included to account for persistent cross-country heterogeneity and common shocks over time. The baseline model is specified as follows:

$$CE_{it} = \beta_0 + \beta_1 FD_{it} + \beta_2 IQ_{it} + \beta_3 GDPG_{it} + \beta_4 FDI_{it} + \beta_5 INF_{it} + \beta_6 UNE_{it} + \beta_7 UR_{it} + \beta_8 INT_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In Eq 1, CE_{it} denotes the circular economy index for country i in year t . FD_{it} represents financial development, measured by domestic credit to the private sector as a percentage of GDP, while IQ_{it} denotes institutional quality. $GDPG_{it}$ is economic growth, FDI_{it} is foreign direct investment, INF_{it} is inflation, UNE_{it} is unemployment, UR_{it} is urbanization, and INT_{it} is Internet use. The term μ_i captures country-specific effects that absorb time-invariant characteristics such as geography, historical institutional structures, and other persistent national features. The term λ_t captures time-specific effects, including common global shocks and trends that affect all countries in a given year, while ε_{it} is the idiosyncratic error term.

Institutional quality is not entered as six governance dimensions simultaneously. Instead, the model is estimated through six separate institutional specifications in which IQ_{it} is represented, one at

a time, by Control of Corruption (CC), Government Effectiveness (GE), Political Stability (PS), Rule of Law (RL), Regulatory Quality (RQ), and Voice and Accountability (VA). This specification strategy enables the relationship between financial development and circular economy performance to be evaluated under alternative institutional settings without mechanically combining highly related governance dimensions in the same regression.

Equivalently, the six specifications can be represented compactly by replacing IQ_{it} in Equation (1) with $IQ_{it}^{(k)}$, where $k \in \{CC, GE, PS, RL, RQ, VA\}$. In each specification, the remaining explanatory variables and the country and time effects are held conceptually constant, enabling the estimated FD coefficient to be compared across institutional dimensions.

The variables used in the empirical model are summarized in Table 2.

Table 2. Description of variables in the model of financial development and circular economy.

Variable group	Symbol	Description	Measurement	References	Data source
Dependent variable	CE	Circular economy index	Composite index constructed by PCA from CAE, EE, ET and RE	Calculated by PCA	Calculated by PCA
Independent variable	FD	Financial development	Domestic credit to the private sector (% of GDP)	Hung et al. (2026); Dinh and Oanh (2026)	WDI
Control variable	IQ	Institutional quality	A composite index constructed from six governance dimensions: control of corruption (CC), government effectiveness (GE), political stability (PS), regulatory quality (RQ), rule of law (RL), and voice and accountability (VA).	Kaufmann et al. (2010); Wiedenhofer et al. (2025); Tuyet and Dinh (2025)	WGI
	GDPG	Economic growth	GDP per capita growth (%)	Hung et al. (2026)	WDI
	FDI	Foreign direct investment	Net FDI (% of GDP)	Wang et al. (2021)	WDI
	INF	Inflation	CPI growth rate (%)	Cai et al. (2024)	WDI
	UNE	Unemployment	Unemployment rate (% of labor force)	Mukherjee et al. (2025)	WDI
	UR	Urbanization	Urban population (% of total population)	Hung et al. (2026)	WDI
	INT	Internet use	Individuals using the Internet (% of population)	Al-Khatib (2023)	WDI

Source: Authors' compilation.

3.6. Estimation method

We use Bayesian regression as the main estimation framework because the international panel contains substantial heterogeneity in economic structure, financial systems, technological capacity, energy systems, and patterns of resource use. In this setting, Bayesian estimation is useful because it provides the full posterior distribution of each parameter rather than relying only on point estimates and conventional significance levels. This permits direct assessment of parameter uncertainty and enables the analysis to report posterior probabilities such as $P(\beta > 0)$ and $P(\beta < 0)$. These probabilities are particularly informative for comparing the direction and stability of the financial-development coefficient across developed and developing economies (Gelman et al., 2013; Greenberg, 2013). The Bayesian framework is used to evaluate posterior evidence regarding the association between financial development and circular economy performance; it is not assumed to eliminate endogeneity, omitted-variable bias, or other panel-data problems automatically.

Conditional on the regressors and parameters, the dependent variable is assumed to follow a Gaussian sampling distribution. Let y denote the stacked vector of CE observations and X the corresponding design matrix. The sampling model is:

$$y | X, \beta, \sigma^2 \sim N(X\beta, \sigma^2 I) \quad (2)$$

Under this assumption, the likelihood function is proportional to:

$$L(\beta, \sigma^2 | y, X) \propto (\sigma^2)^{-n/2} \exp\left\{-\frac{1}{2\sigma^2}(y - X\beta)'(y - X\beta)\right\} \quad (3)$$

The baseline Bayesian estimation uses a standard Normal prior for the regression coefficients. Specifically, each coefficient is assigned a zero-centered prior:

$$\beta_j \sim N(0, 1), \quad j = 0, 1, \dots, 8 \quad (4)$$

The zero-centered prior does not impose an a priori positive or negative relationship between financial development and circular economy performance, while the unit variance provides moderate regularization. Bayesian inference combines the likelihood with the prior distribution through Bayes' theorem. In general, the posterior distribution is proportional to the product of the likelihood and the prior:

$$P(\beta | y, X) \propto L(\beta | y, X) p(\beta) \quad (5)$$

Posterior inference is summarized using the posterior mean, posterior standard deviation, posterior probabilities $P(\beta > 0)$ and $P(\beta < 0)$, and Monte Carlo error. These statistics enable the analysis to assess the magnitude of the estimated coefficient and the posterior certainty regarding its direction. When reported, the 95% credible interval is defined by the 2.5th and 97.5th percentiles of the posterior distribution.

To benchmark the Bayesian results, we also employ Pooled OLS, FEM, REM, and Two-way FEM as conventional panel-data benchmarks. These estimators provide complementary evidence on whether the sign and magnitude of the FD coefficient remain broadly stable under alternative treatments of unobserved country heterogeneity and common time effects. They are used for comparison and robustness purposes rather than as substitutes for the Bayesian framework.

The reliability of the baseline findings is further examined through several additional robustness procedures. These include the Durbin-Wu-Hausman endogeneity test, the Oster coefficient-stability test for omitted-variable bias, the use of Material Flow as an alternative measure of circular economy performance, a one-year lag of financial development, exclusion of the Global Financial Crisis period, exclusion of the COVID-19 period, exclusion of both crisis episodes, and prior sensitivity analysis. For the latter, the baseline standard prior $N(0, 1)$ is compared with two alternative specifications: A weak prior $N(0, 10^2)$ and a shrinkage prior $N(0, 0.5^2)$. This comparison assesses whether the sign, magnitude, and posterior certainty of the FD coefficient are sensitive to changes in prior dispersion. Together, these robustness checks evaluate sensitivity to potential endogeneity, omitted-variable bias, alternative outcome measurement, temporal specification, major global shocks, and prior assumptions.

Based on the theoretical arguments and empirical specification discussed above, Figure 1 summarizes the conceptual framework of the study. Financial development may be associated with circular economy performance through supporting and constraining channels, while the strength and direction of this relationship may differ between developed and developing countries.

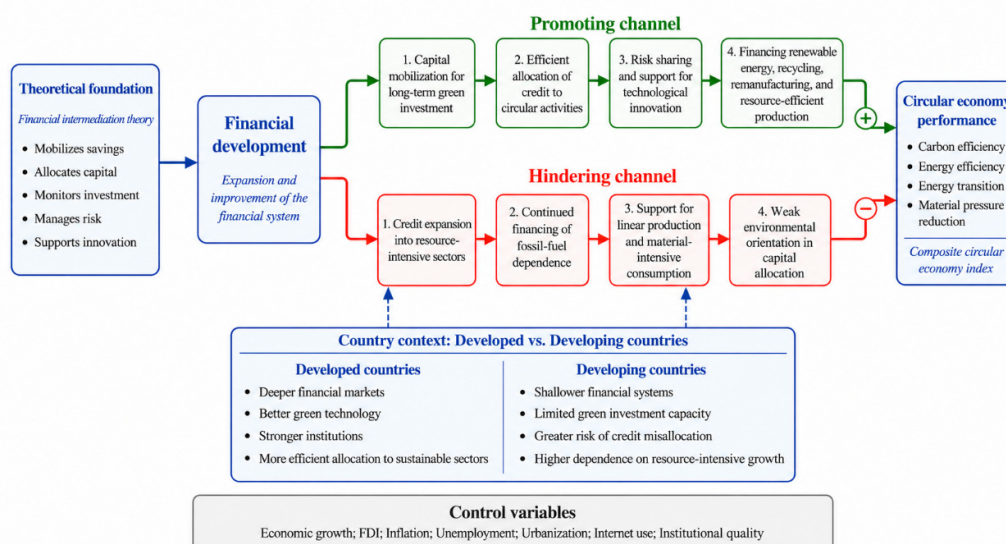


Figure 1. Conceptual framework of the impact of financial development on the circular economy.

4. Results

4.1. Construction of the circular economy index

Before constructing the composite index, the suitability of the data is evaluated using KMO and Bartlett tests. Table 3 shows that the KMO value is 0.7620, which indicates good suitability for principal component analysis. Bartlett's test has a chi square value of 3641.76 with a p-value of 0.0000, enabling rejection of the null hypothesis that the correlation matrix is an identity matrix. The component variables therefore share enough common variance to be reduced to a latent structure representing circular economy performance.

Table 3. KMO and Bartlett tests for sample adequacy.

Test	Statistic	Value	Description
Kaiser–Meyer–Olkin (KMO)	Overall MSA	0.7620	Good
Bartlett test	Chi-square (χ^2)	3641.76	Statistically significant
	p-value	0.0000	Statistically significant

Source: Authors' calculation (2026).

Table 4 shows that the first principal component has an eigenvalue of 2.3149 and explains 57.87 percent of total variance. According to the Kaiser criterion, only PC1 has an eigenvalue greater than 1 and is therefore retained to construct the circular economy index. Although PC2 has an eigenvalue of 0.9706 and explains an additional 24.27 percent of variance, it is not used for the main index because PC1 is the only component exceeding the Kaiser threshold and accounts for the largest share of variance. PC1 also has positive loadings for all four adjusted indicators, indicating that it best captures the common macro level circular economy structure.

Table 4. Principal component analysis results.

Component	Eigenvalue	Variance explained (%)	Cumulative variance (%)
PC1	2.3149	57.87	57.87
PC2	0.9706	24.27	82.14
PC3	0.4870	12.18	94.31
PC4	0.2275	5.69	100.00

Source: Authors' calculation (2026).

The factor loadings in Table 5 show that all four indicators load positively on PC1. Energy transition and energy efficiency have the highest loadings at 0.5939 and 0.5919, respectively. This suggests that energy is a prominent axis of circular transition in the sample. However, reversed carbon efficiency and reversed material pressure also load positively, at 0.4126 and 0.3558, respectively. The index is therefore not reduced to an energy index; it also preserves the two core dimensions of circularity: emission reduction and lower dependence on primary materials.

4.2. Comparison between developed and developing countries

Table 6 presents descriptive statistics of the circular economy index by country group. Developed countries have a mean score of 0.864, much higher than the 0.413 recorded for developing countries. The standard deviation of developed countries is 0.110, lower than the 0.216 of developing countries. This means that developed countries not only have higher circular economy performance but also more

stable results. Developing countries show greater dispersion, reflecting within group differences in technology, energy, environmental infrastructure, and capital mobilization capacity.

Table 5. Factor loadings from principal component analysis.

Variable	PC1	PC2	PC3	PC4
CAE*	0.4126	−0.6460	0.6422	−0.0004
ET	0.5939	−0.0088	0.3732	0.7127
EE	0.5919	−0.0174	−0.3973	0.7011
RE*	0.3558	0.7631	0.5390	0.0238

Source: Authors' calculation (2026). Note: CAE* and RE* are reversed variables before PCA so that higher values indicate better circular economy performance.

Table 6. Descriptive statistics of the circular economy index by country group.

Country group	Number of countries	Mean	Standard deviation	Minimum	Maximum
Developing	79	0.413	0.216	0.000	0.920
Developed	30	0.864	0.110	0.301	1.000

Source: Authors' calculation (2026).

The difference tests in Table 7 confirm this pattern. The Levene test has a p-value below 0.001, indicating unequal variances between the two groups. Therefore, the Welch t-test is more appropriate than the conventional t-test. The Welch statistic is −14.111 with a p-value below 0.001, confirming a statistically significant difference in mean values. The Mann–Whitney U test provides the same conclusion. Thus, the difference in circular economy performance between developed and developing countries is not driven by a single test, but is confirmed by parametric and non-parametric evidence.

Table 7. Tests of differences in the circular economy index between country groups.

Test	Statistic	df	p-value
Levene test for equality of variances	20.551	107	< 0.001
Welch t-test	−14.111	94.756	< 0.001
Mann-Whitney U test	67		< 0.001

Source: Authors' calculation (2026).

Academically, this result shows that circular transition is uneven across country groups. Developed countries have advantages in technology, clean energy, environmental standards, and green finance. However, they face the challenge of high material consumption. Developing countries may have lower average material consumption, but often lack circular infrastructure and technological

capacity for substantive transformation. Circular economy comparison should therefore be situated in the broader development context rather than based solely on one output indicator.

4.3. Relationship between financial development and the circular economy

4.3.1. Bayesian regression results by country group

Tables 8 to 13 present Bayesian regression results for the effect of financial development on the circular economy, using six institutional quality dimensions as controls: control of corruption (CC), government effectiveness (GE), political stability (PS), regulatory quality (RQ), rule of law (RL), and voice and accountability (VA).

Table 8. Bayesian regression results with control of corruption (CC) as the institutional control variable.

Country group	Variable	Posterior mean	Posterior standard deviation	Probability > 0	Probability < 0	Monte Carlo error
Developed	C	0.1678	0.0164	1.0000	0.0000	0.0001
	GDP	0.0039	0.0009	1.0000	0.0000	0.0000
	FDI	-0.0003	0.0007	0.3201	0.6799	0.0000
	UR	0.0027	0.0003	1.0000	0.0000	0.0000
	INF	0.0000	0.0002	0.4050	0.5950	0.0000
	UNE	0.0028	0.0007	1.0000	0.0000	0.0000
	INT	0.0003	0.0002	0.9492	0.0508	0.0000
	FD	0.0021	0.0001	1.0000	0.0000	0.0000
	CC	0.0608	0.0074	1.0000	0.0000	0.0000
Developing	C	0.8309	0.0317	1.0000	0.0000	0.0002
	GDP	-0.0018	0.0011	0.0466	0.9534	0.0000
	FDI	-0.0002	0.0001	0.0129	0.9871	0.0000
	UR	-0.0002	0.0004	0.3092	0.6908	0.0000
	INF	-0.0076	0.0015	0.0000	1.0000	0.0000
	UNE	0.0007	0.0012	0.7356	0.2644	0.0000
	INT	-0.0007	0.0002	0.0011	0.9989	0.0000
	FD	-0.0001	0.0001	0.2051	0.7949	0.0000
	CC	0.0775	0.0080	1.0000	0.0000	0.0000

Source: Authors' calculation.

Table 9. Bayesian regression results with government effectiveness (GE) as the institutional control variable.

Country group	Variable	Posterior mean	Posterior standard deviation	Probability > 0	Probability < 0	Monte Carlo error
Developed	C	0.1976	0.0164	1.0000	0.0000	0.0002
	GDP	0.0036	0.0009	1.0000	0.0000	0.0000
	FDI	−0.0005	0.0007	0.2094	0.7906	0.0000
	UR	0.0026	0.0002	1.0000	0.0000	0.0000
	INF	0.0001	0.0002	0.6302	0.3698	0.0000
	UNE	0.0035	0.0006	1.0000	0.0000	0.0000
	INT	−0.0001	0.0002	0.2340	0.7660	0.0000
	FD	0.0017	0.0002	1.0000	0.0000	0.0000
	GE	0.0944	0.0086	1.0000	0.0000	0.0000
Developing	C	0.7996	0.0308	1.0000	0.0000	0.0002
	GDP	−0.0017	0.0010	0.0520	0.9480	0.0000
	FDI	−0.0001	0.0001	0.0139	0.9861	0.0000
	UR	−0.0007	0.0004	0.0279	0.9721	0.0000
	INF	−0.0055	0.0015	0.0001	0.9999	0.0000
	UNE	0.0023	0.0011	0.9781	0.0219	0.0000
	INT	−0.0008	0.0002	0.0004	0.9996	0.0000
	FD	0.0001	0.0001	0.8107	0.1893	0.0000
	GE	0.1194	0.0099	1.0000	0.0000	0.0001

Source: Authors' calculation.

Overall, the group specific results show that financial development has a positive, stable, and highly certain effect in developed countries. In this group, the financial development coefficient is positive in all non-interaction models, and the posterior probability of a positive effect reaches 1.0000. This implies that financial systems in developed economies are better able to transform capital into investments that support the circular economy. Banks, capital markets, investment funds, and insurers can finance clean technologies, high-quality recycling, reverse logistics, renewable energy, and business models that extend product life cycles.

In developing countries, the results are less stable. The financial development coefficient is positive but very small in some models and negative in others. This reflects the limits of financial development when capital flows are not directed toward circular activities. In many developing economies, credit may be concentrated in heavy industry, mining, real estate, construction, or fossil energy. In such cases, financial expansion can increase material pressure and emissions rather than improve circular economy performance.

This result supports a cautious interpretation of finance in sustainable development: Finance is necessary, but it is not sufficient when the quality of capital allocation is weak.

Table 10. Bayesian regression results with political stability (PS) as the institutional control variable.

Country group	Variable	Posterior mean	Posterior standard deviation	Probability > 0	Probability < 0	Monte Carlo error
Developed	C	0.1141	0.0159	1.0000	0.0000	0.0001
	GDP	0.0038	0.0010	1.0000	0.0000	0.0000
	FDI	−0.0003	0.0007	0.3096	0.6904	0.0000
	UR	0.0030	0.0003	1.0000	0.0000	0.0000
	INF	−0.0002	0.0002	0.2312	0.7688	0.0000
	UNE	0.0032	0.0007	1.0000	0.0000	0.0000
	INT	0.0004	0.0002	0.9755	0.0245	0.0000
	FD	0.0023	0.0001	1.0000	0.0000	0.0000
	PS	0.0187	0.0062	0.9982	0.0018	0.0000
Developing	C	0.8818	0.0360	1.0000	0.0000	0.0002
	GDP	−0.0017	0.0011	0.0624	0.9376	0.0000
	FDI	−0.0003	0.0001	0.0001	0.9999	0.0000
	UR	0.0004	0.0004	0.8653	0.1347	0.0000
	INF	−0.0100	0.0016	0.0000	1.0000	0.0000
	UNE	−0.0063	0.0012	0.0000	1.0000	0.0000
	INT	0.0001	0.0002	0.6472	0.3528	0.0000
	FD	−0.0005	0.0001	0.0000	1.0000	0.0000
	PS	0.0412	0.0094	1.0000	0.0000	0.0001

Source: Authors' calculation.

Table 11. Bayesian regression results with rule of law (RL) as the institutional control variable.

Country group	Variable	Posterior mean	Posterior standard deviation	Probability > 0	Probability < 0	Monte Carlo error
Developed	C	0.1993	0.0165	1.0000	0.0000	0.0002
	GDP	0.0035	0.0009	1.0000	0.0000	0.0000
	FDI	−0.0007	0.0007	0.1378	0.8622	0.0000
	UR	0.0025	0.0002	1.0000	0.0000	0.0000
	INF	0.0001	0.0002	0.6526	0.3474	0.0000
	UNE	0.0025	0.0006	1.0000	0.0000	0.0000
	INT	0.0002	0.0002	0.9153	0.0847	0.0000
	FD	0.0020	0.0001	1.0000	0.0000	0.0000
	RL	0.0888	0.0081	1.0000	0.0000	0.0001
Developing	C	0.7727	0.0316	1.0000	0.0000	0.0002
	GDP	−0.0013	0.0010	0.1016	0.8984	0.0000
	FDI	−0.0002	0.0001	0.0012	0.9988	0.0000
	UR	0.0001	0.0004	0.6002	0.3998	0.0000
	INF	−0.0074	0.0015	0.0000	1.0000	0.0000
	UNE	0.0016	0.0011	0.9117	0.0883	0.0000
	INT	−0.0008	0.0002	0.0000	1.0000	0.0000
	FD	0.0001	0.0001	0.6998	0.3002	0.0000
	RL	0.1134	0.0105	1.0000	0.0000	0.0001

Source: Authors' calculation.

4.3.2. Trace plots, posterior density, and autocorrelation in the Bayesian model

MCMC diagnostic plots are used to evaluate the stability of simulation chains before interpreting posterior coefficients. In principle, trace plots show whether MCMC chains fluctuate around a stable value region. If chains do not exhibit persistent drift and mix well, the MCMC algorithm shows reasonable convergence (Gelman et al., 2013; Kruschke, 2015). Posterior density plots indicate whether parameter distributions are concentrated on the positive side, the negative side, or close to zero, thereby helping evaluate the probability and certainty of the direction of effect rather than relying only on frequentist significance thresholds (Greenberg, 2013). Autocorrelation plots show the dependence of MCMC samples across lags; autocorrelation that declines quickly toward zero is a favorable sign because posterior samples are relatively more independent (Chib and Greenberg, 1995; Gelman et al., 2013).

The diagnostic plots generally indicate acceptable stability of the simulation chains. Trace plots fluctuate around relatively stable regions and do not show long persistent drift. Posterior density plots are relatively smooth, suggesting that the simulated samples generate clear posterior distributions. Autocorrelation declines across lags, implying that dependence among samples is not excessive. The posterior results reported in the regression tables can therefore be considered reliable (Figures 2–13).

Table 12. Bayesian regression results with regulatory quality (RQ) as the institutional control variable.

Country group	Variable	Posterior mean	Posterior standard deviation	Probability > 0	Probability < 0	Monte Carlo error
Developed	C	0.2137	0.0158	1.0000	0.0000	0.0001
	GDP	0.0036	0.0009	1.0000	0.0000	0.0000
	FDI	−0.0011	0.0007	0.0427	0.9573	0.0000
	UR	0.0022	0.0002	1.0000	0.0000	0.0000
	INF	0.0003	0.0002	0.9356	0.0644	0.0000
	UNE	0.0029	0.0006	1.0000	0.0000	0.0000
	INT	0.0002	0.0002	0.8057	0.1943	0.0000
	FD	0.0017	0.0001	1.0000	0.0000	0.0000
	RQ	0.1071	0.0079	1.0000	0.0000	0.0000
Developing	C	0.7625	0.0323	1.0000	0.0000	0.0002
	GDP	−0.0026	0.0011	0.0080	0.9920	0.0000
	FDI	−0.0002	0.0001	0.0029	0.9971	0.0000
	UR	−0.0002	0.0004	0.3277	0.6723	0.0000
	INF	−0.0079	0.0015	0.0000	1.0000	0.0000
	UNE	0.0013	0.0012	0.8676	0.1324	0.0000
	INT	−0.0003	0.0002	0.0677	0.9323	0.0000
	FD	0.0001	0.0001	0.8484	0.1516	0.0000
	RQ	0.1038	0.0106	1.0000	0.0000	0.0001

Source: Authors' calculation.

Table 13. Bayesian regression results with voice and accountability (VA) as the institutional control variable.

Country group	Variable	Posterior mean	Posterior standard deviation	Probability > 0	Probability < 0	Monte Carlo error
Developed	C	0.1579	0.0147	1.0000	0.0000	0.0001
	GDP	0.0038	0.0009	1.0000	0.0000	0.0000
	FDI	−0.0006	0.0007	0.1823	0.8177	0.0000
	UR	0.0027	0.0002	1.0000	0.0000	0.0000
	INF	0.0001	0.0002	0.6134	0.3866	0.0000
	UNE	0.0020	0.0007	0.9991	0.0009	0.0000
	INT	0.0005	0.0002	0.9975	0.0025	0.0000
	FD	0.0023	0.0001	1.0000	0.0000	0.0000
	VA	0.0661	0.0063	1.0000	0.0000	0.0000
Developing	C	0.7197	0.0340	1.0000	0.0000	0.0002
	GDP	−0.0008	0.0011	0.2233	0.7767	0.0000
	FDI	−0.0002	0.0001	0.0001	0.9999	0.0000
	UR	0.0013	0.0004	0.9998	0.0002	0.0000
	INF	−0.0092	0.0015	0.0000	1.0000	0.0000
	UNE	−0.0018	0.0011	0.0503	0.9497	0.0000
	INT	−0.0007	0.0002	0.0011	0.9989	0.0000
	FD	0.0001	0.0001	0.9066	0.0934	0.0000
	VA	0.0937	0.0104	1.0000	0.0000	0.0001

Source: Authors' calculation.

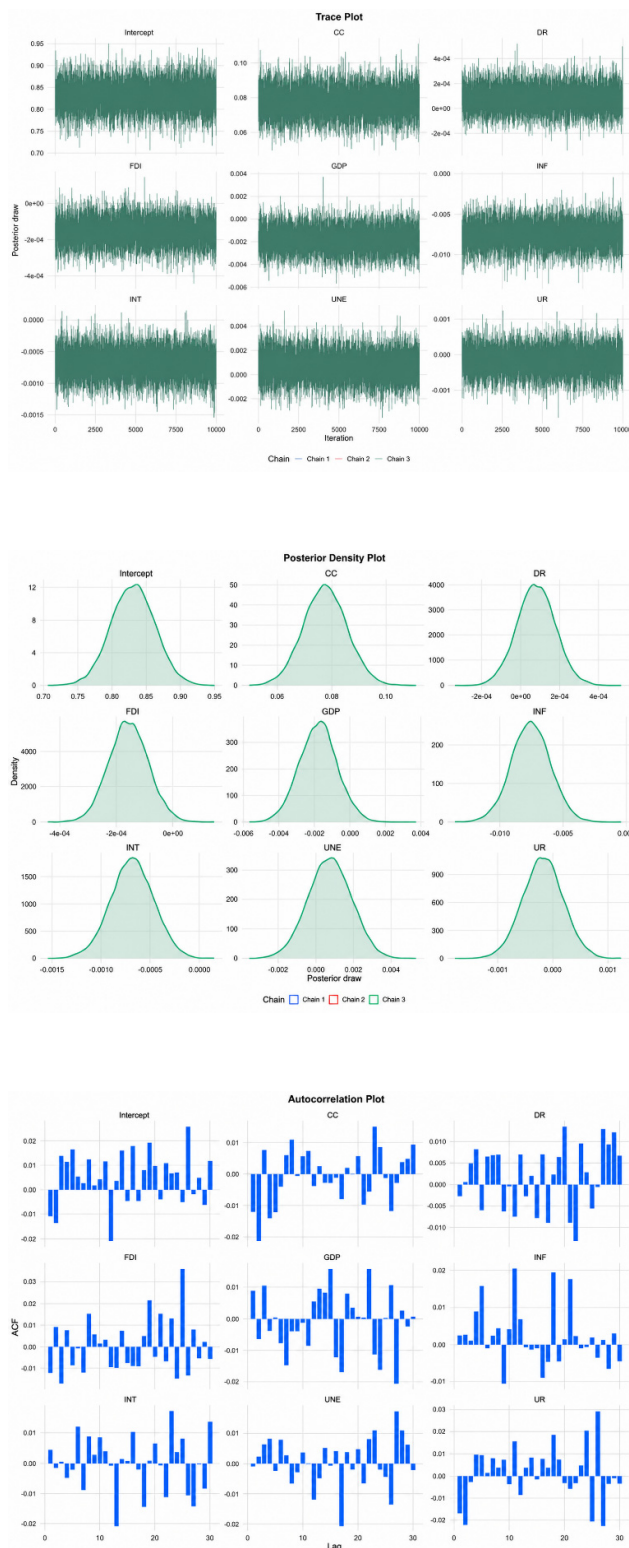


Figure 2. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for control of corruption (CC) for developed countries. Source: Authors' calculation.

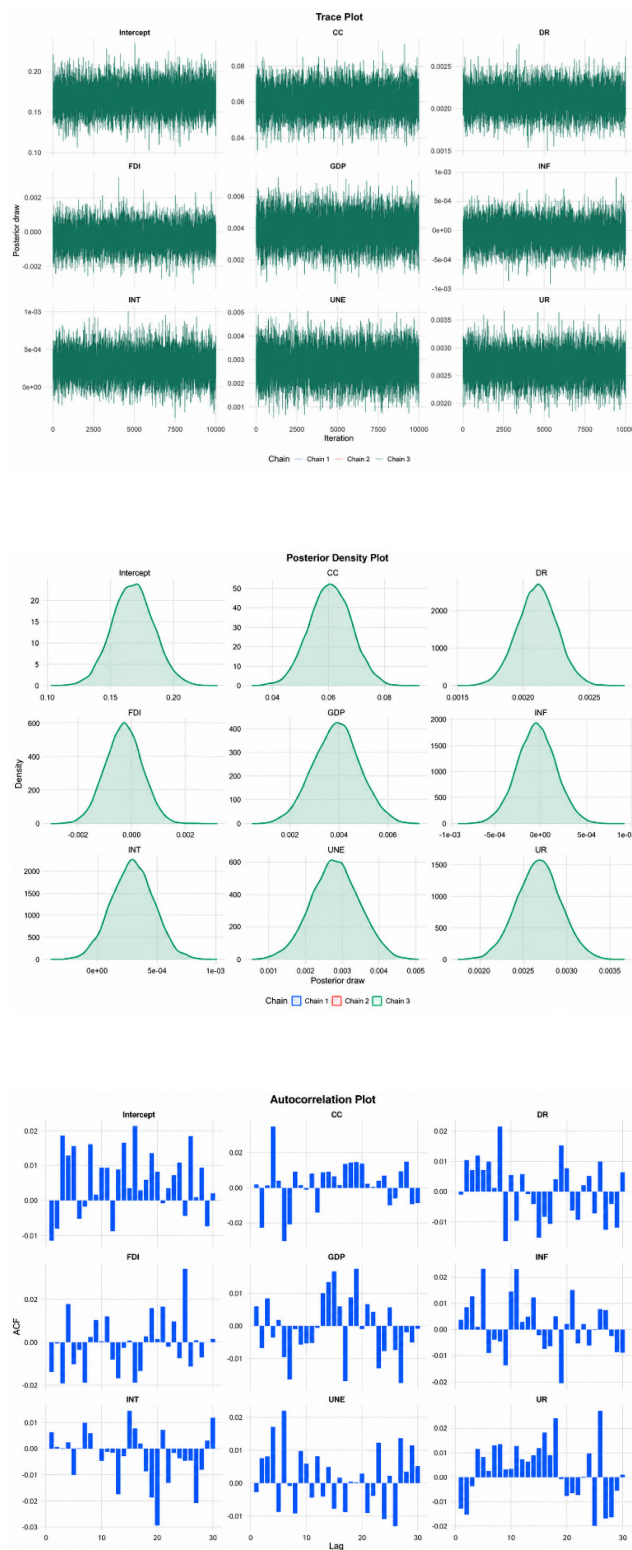


Figure 3. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for control of corruption (CC) for developing countries. Source: Authors' calculation.

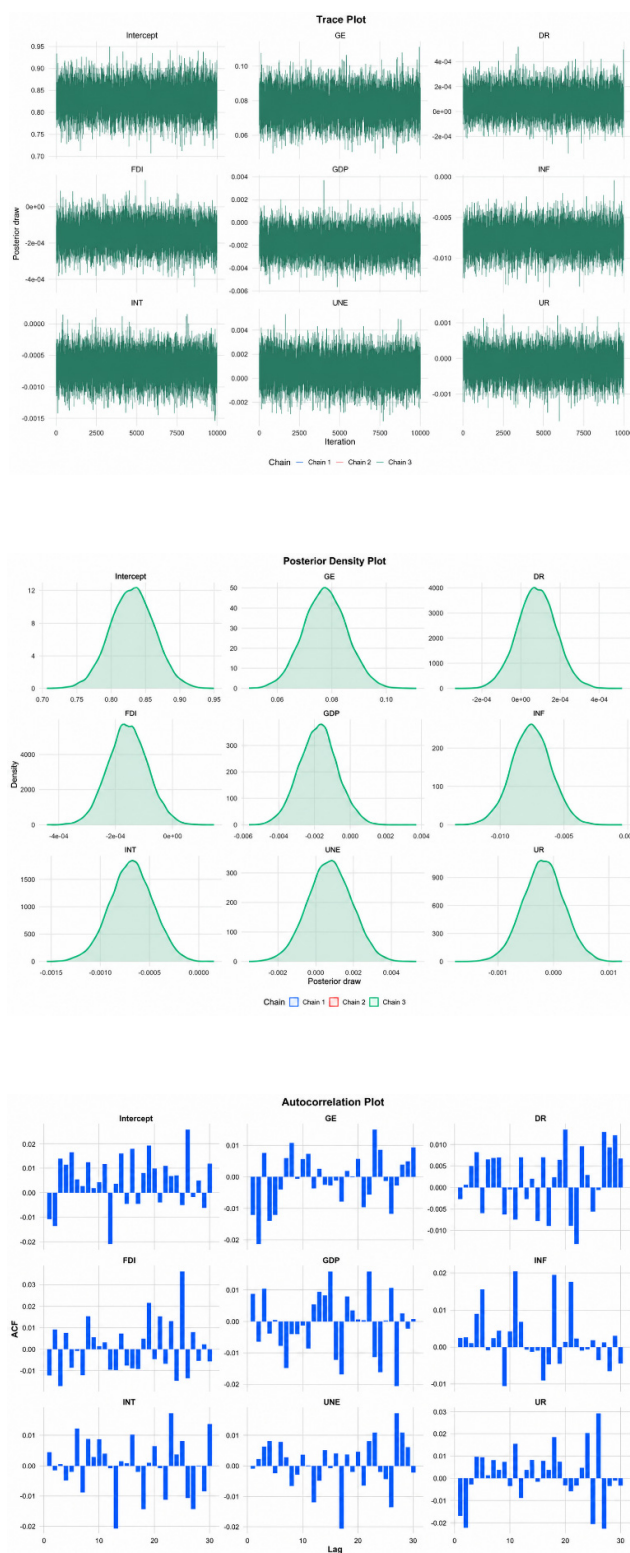


Figure 4. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for government effectiveness (GE) for developed countries. Source: Authors' calculation.

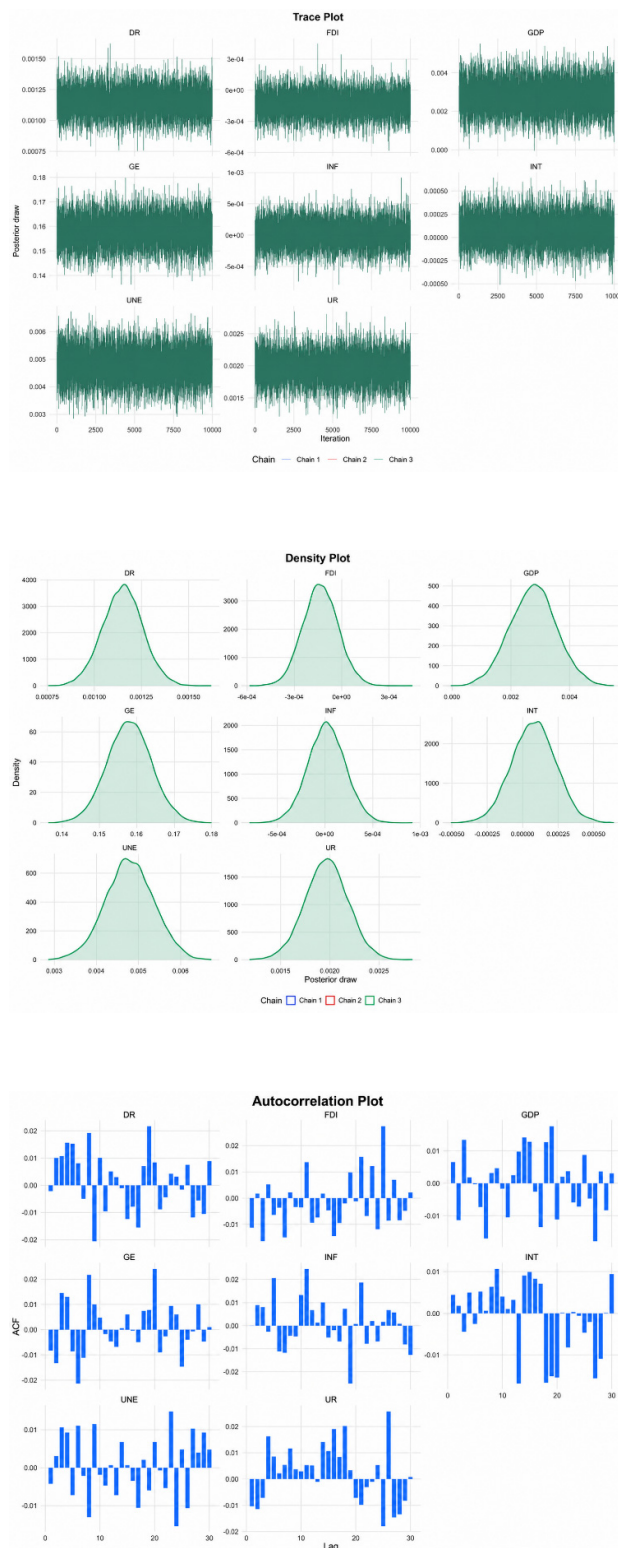


Figure 5. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for government effectiveness (GE) for developing countries. Source: Authors' calculation.

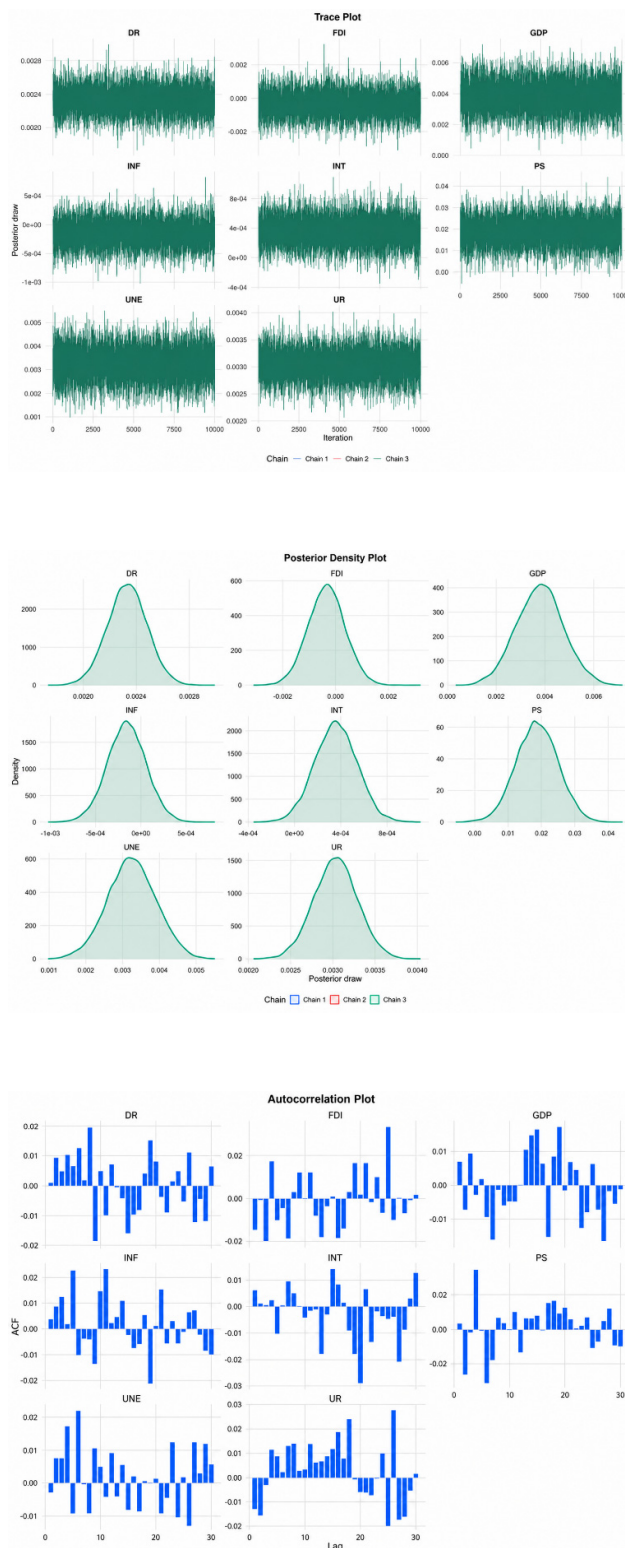


Figure 6. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for political stability (PS) for developed countries. Source: Authors' calculation.

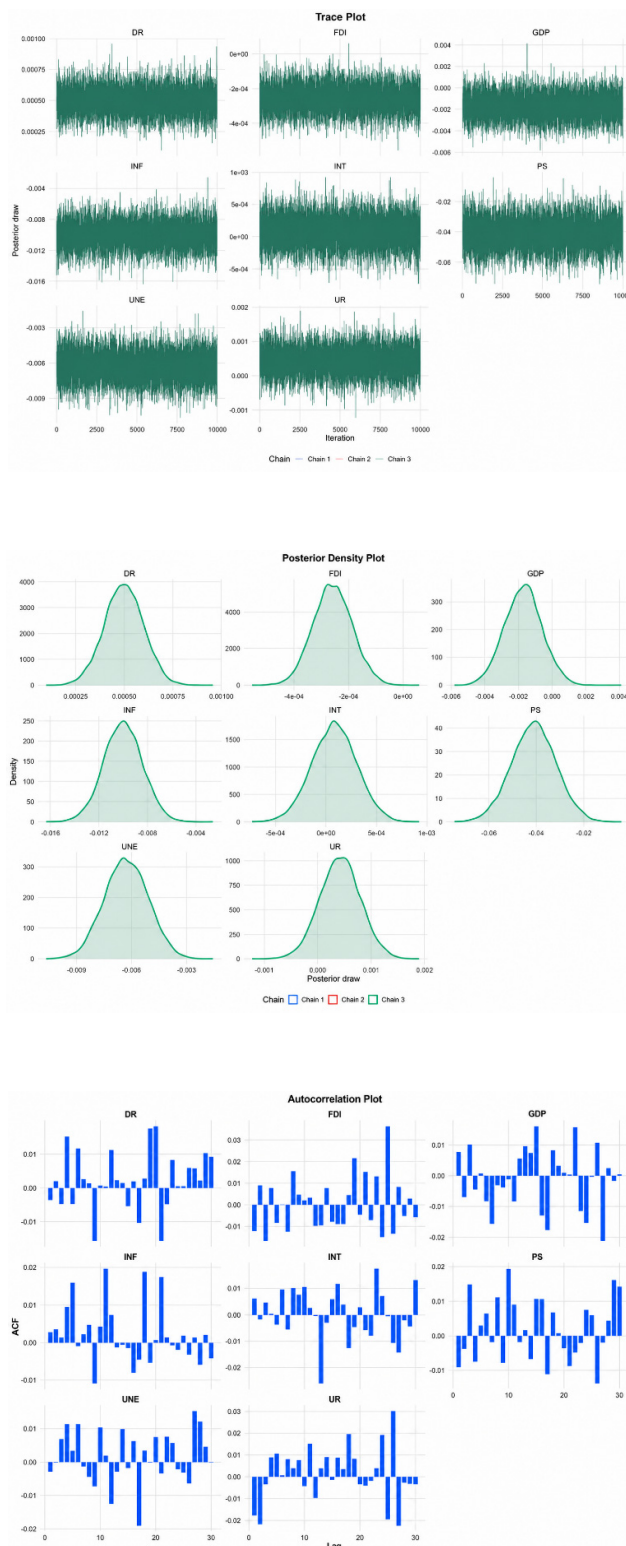


Figure 7. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for political stability (PS) for developing countries. Source: Authors' calculation.

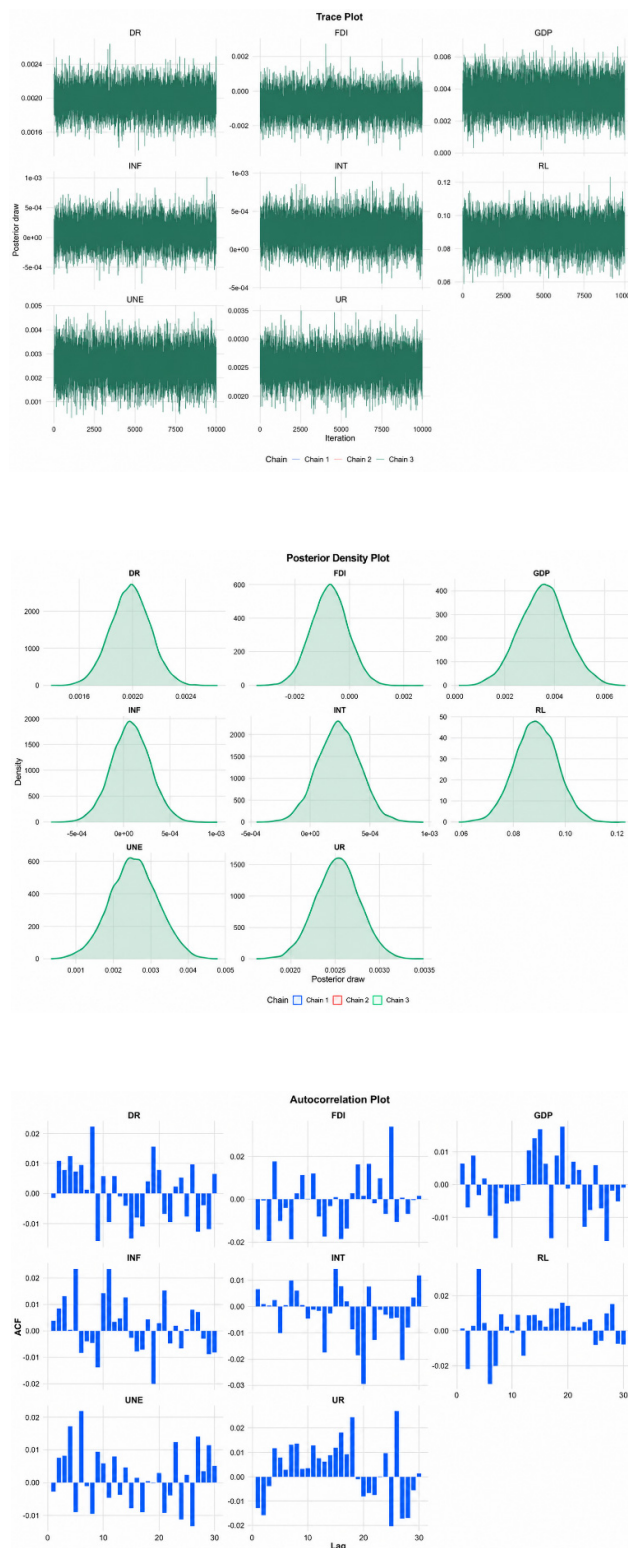


Figure 8. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for rule of law (RL) for developed countries. Source: Authors' calculation.

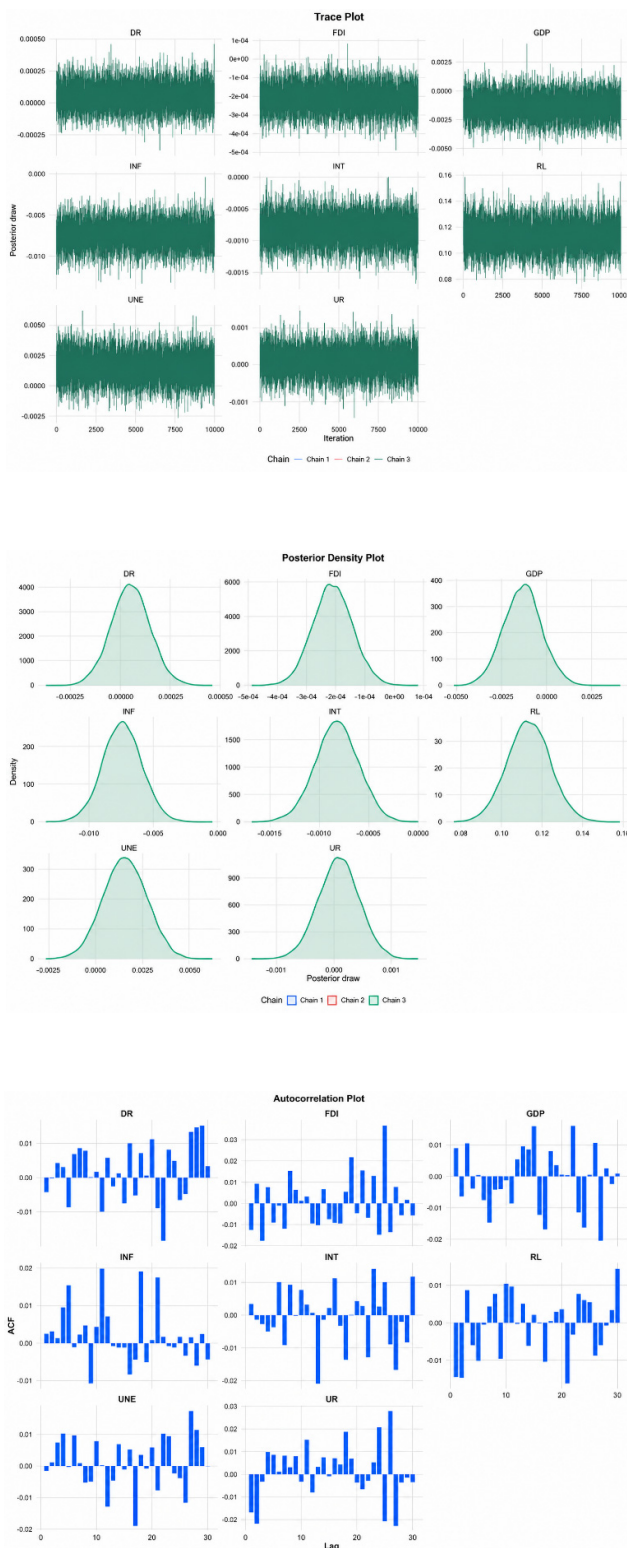


Figure 9. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for rule of law (RL) for developing countries. Source: Authors' calculation.

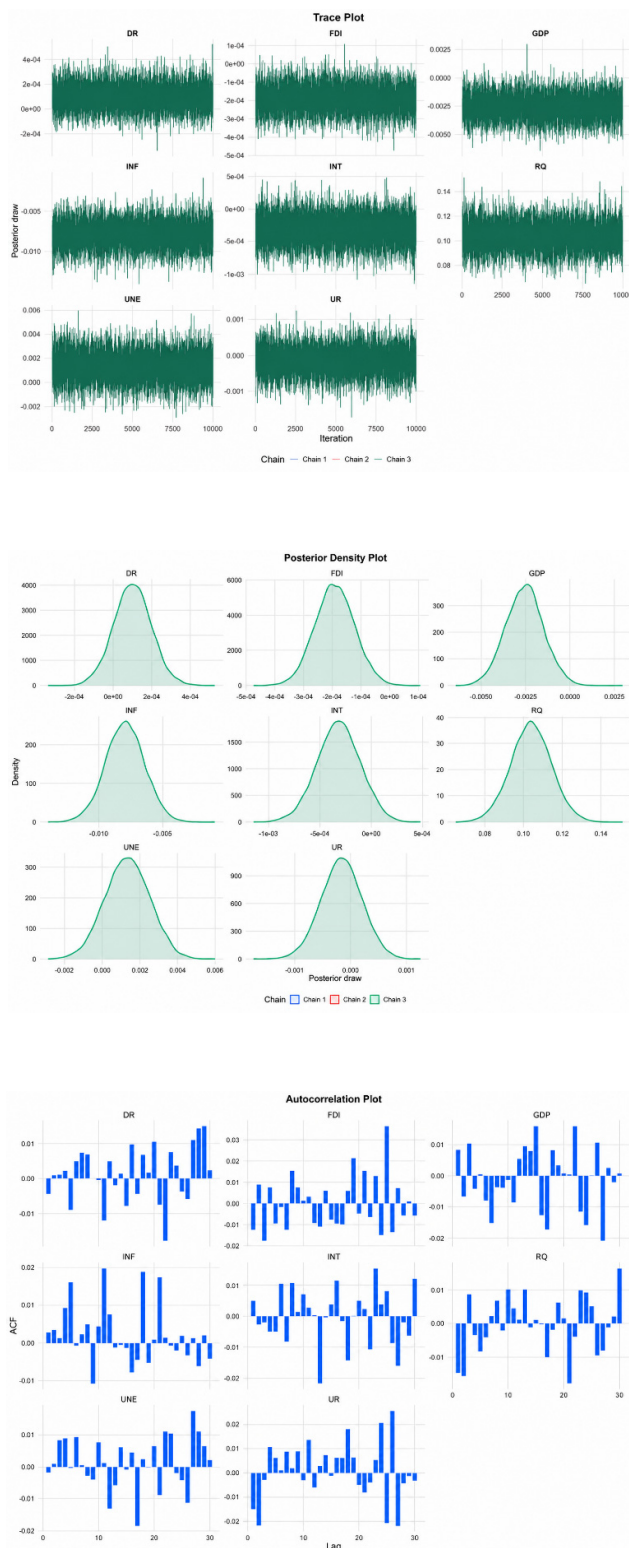


Figure 10. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for regulatory quality (RQ) for developed countries. Source: Authors' calculation.

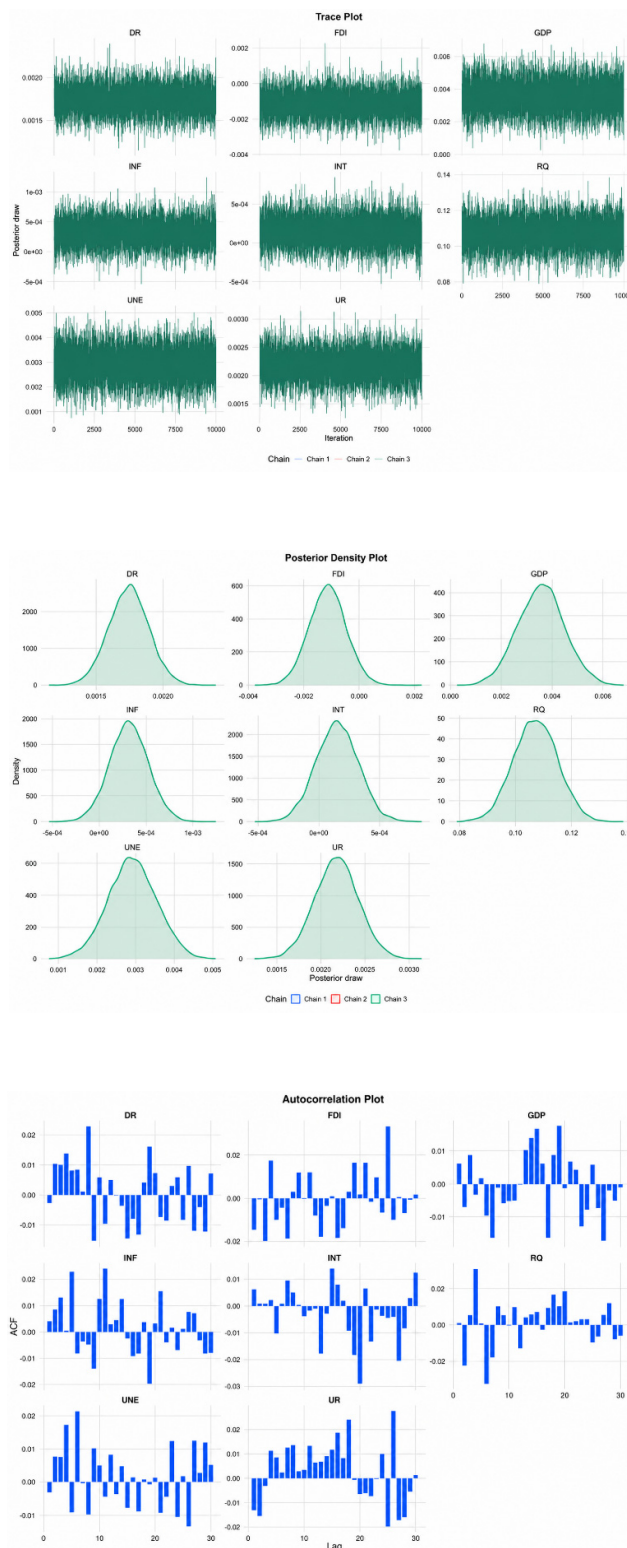


Figure 11. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for regulatory quality (RQ) for developing countries. Source: Authors' calculation.

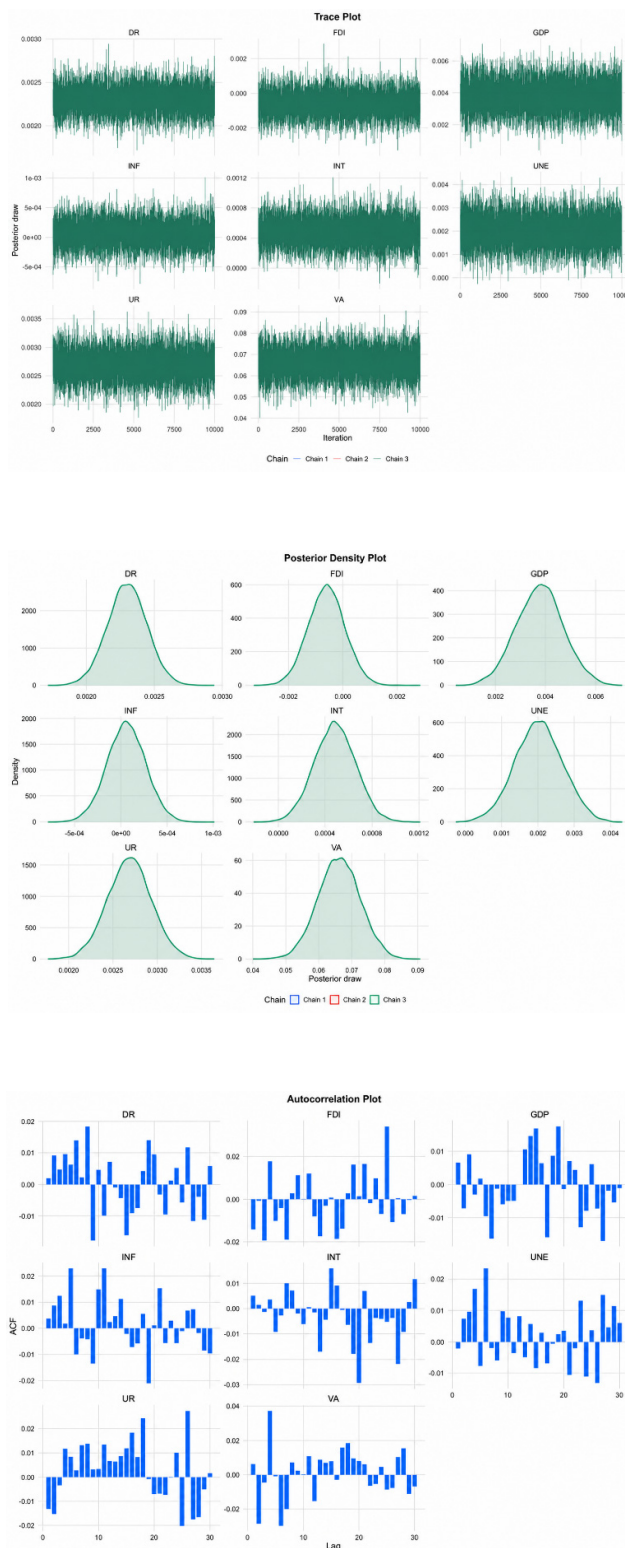


Figure 12. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for voice and accountability (VA) for developed countries. Source: Authors' calculation.

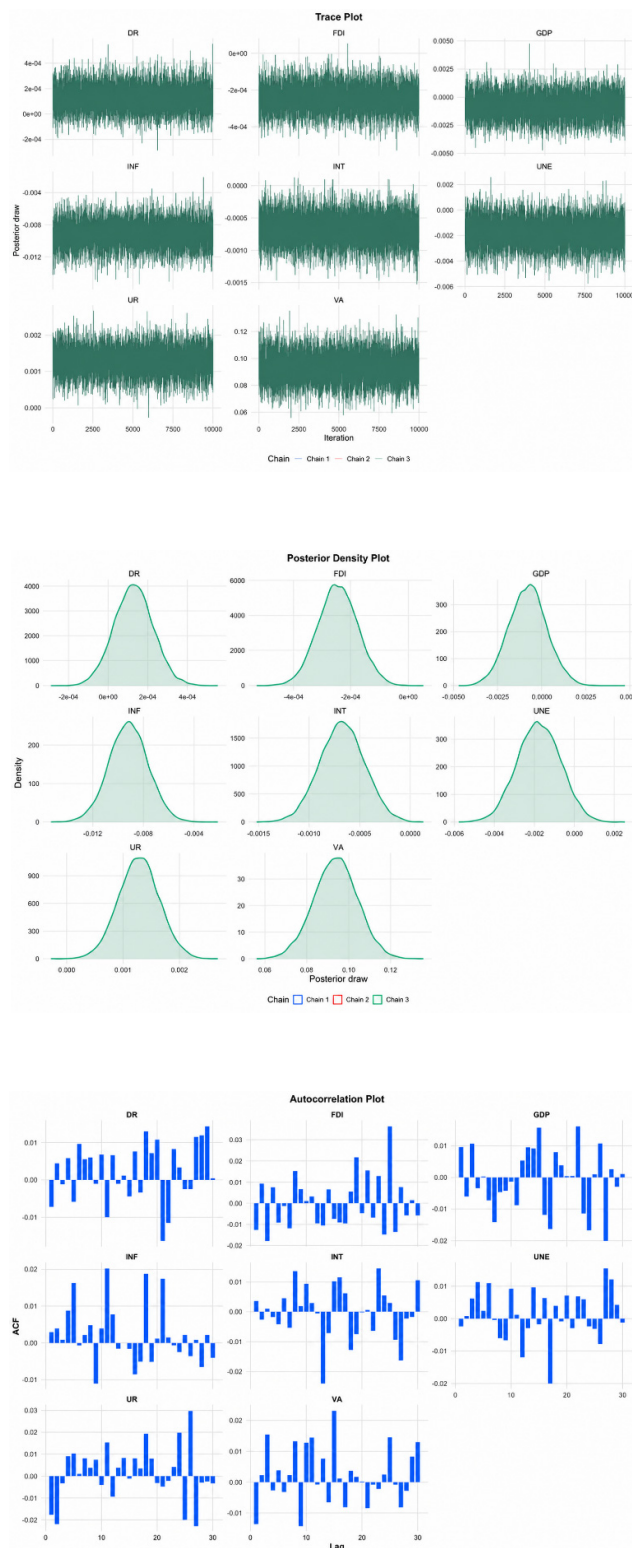


Figure 13. Trace plots, posterior density plots, and autocorrelation plots of the Bayesian model controlling for voice and accountability (VA) for developing countries. Source: Authors' calculation.

4.3.3. Durbin–Wu–Hausman endogeneity test

Potential endogeneity may arise when an explanatory variable is correlated with the structural error term, which can lead to biased and inconsistent coefficient estimates. To assess whether financial development suffers from this problem, we apply the Durbin–Wu–Hausman (DWH) endogeneity test following the instrumental-variable specification. The DWH procedure is widely used to assess whether a potentially endogenous regressor can be treated as exogenous by comparing estimates that are consistent under different assumptions regarding regressor–error correlation (Durbin, 1954; Wu, 1973; Hausman, 1978). The null hypothesis of the test is that financial development is exogenous and therefore uncorrelated with the structural error term. The alternative hypothesis indicates that financial development is endogenous. Accordingly, rejection of the null hypothesis would provide evidence that endogeneity should be explicitly addressed in the empirical specification.

As reported in Table 14, the Durbin–Wu–Hausman tests provide no statistically significant evidence of endogeneity in either country group. For developed countries, the Durbin score χ^2 statistic is 1.84 with a p-value of 0.175, while the Wu–Hausman F statistic is 1.79 with a p-value of 0.182. For developing countries, the corresponding statistics are 2.06 ($p = 0.151$) and 1.97 ($p = 0.161$), respectively. Since all p-values exceed conventional significance levels, the null hypothesis of exogeneity cannot be rejected for either group. These results suggest that financial development does not exhibit statistically detectable endogeneity in the group-specific specifications.

Table 14. Durbin–Wu–Hausman endogeneity test.

Country group	Test	Statistic	p-value	Decision
Developed	Durbin score χ^2 test	1.84	0.175	Do not reject H_0
	Wu–Hausman F test	1.79	0.182	Do not reject H_0
Developing	Durbin score χ^2 test	2.06	0.151	Do not reject H_0
	Wu–Hausman F test	1.97	0.161	Do not reject H_0

Source: Authors' calculation.

4.3.4. Oster coefficient-stability test for omitted-variable bias

Potential omitted-variable bias may arise when unobserved factors are correlated with financial development and circular economy performance, causing the estimated coefficient to be biased. To assess the sensitivity of the baseline results to this concern, we apply the coefficient-stability approach proposed by Oster (2019). The purpose of this test is to examine whether the estimated effect of financial development remains stable as additional observed controls are introduced and to evaluate how strong selection on unobserved factors would need to be, relative to selection on observables, to eliminate the estimated effect.

The procedure compares the coefficient of financial development and the model fit between a restricted specification and a full-control specification. It then derives a bias-adjusted coefficient and

the parameter δ , where δ measures the proportional strength of selection on un-observables relative to observables required to drive the estimated coefficient to zero.

As reported in Table 15, the coefficient on financial development remains positive when moving from the restricted model to the full-control specification, declining only from 0.0028 to 0.0021, while R^2 increases from 0.412 to 0.568. Using an assumed $R_{\max}$ of 0.738, the Oster bias-adjusted coefficient is 0.0017 and remains positive. The estimated δ is 2.36, indicating that selection on unobserved factors would need to be approximately 2.36 times as strong as selection on the included observables to reduce the estimated financial development effect to zero.

As reported in Table 15, the coefficient on financial development remains positive after the inclusion of additional controls in both country groups. For developed countries, the coefficient declines from 0.0028 to 0.0021 as R^2 increases from 0.412 to 0.568. Using an $R_{\max}$ of 0.738, the bias-adjusted coefficient remains positive at 0.0017, while the estimated δ is 2.36. For developing countries, the coefficient decreases from 0.0019 to 0.0014 as R^2 rises from 0.365 to 0.497. With an $R_{\max}$ of 0.646, the bias-adjusted coefficient remains positive at 0.0011 and δ equals 1.74. Since the estimated $|\delta|$ values exceed 1 in both groups, the results suggest that the estimated effect of financial development is relatively robust to potential omitted-variable bias. The larger δ for developed countries also indicates greater coefficient stability in this group.

Table 15. Oster (2019) coefficient-stability test for omitted variable bias.

Country group	Specification	β (FD)	R^2	$R_{\max}$	Bias-adjusted β	δ
Developed	Restricted controls	0.0028	0.412	—	—	—
	Full controls	0.0021	0.568	0.738	0.0017	2.36
Developing	Restricted controls	0.0019	0.365	—	—	—
	Full controls	0.0014	0.497	0.646	0.0011	1.74

Source: Authors' calculation.

4.3.5. Robustness using Material Flow as an alternative measure of circular economy performance

The first robustness test examines whether the baseline findings depend on the measurement of circular economy performance. The PCA-based Circular Economy Index is replaced with Material Flow (MF), which captures material pressure more directly. The use of material flows as an alternative proxy for circular economy performance is well established in the literature. Haas et al. (2020) assessed the circularity of the global economy and the European Union by tracing economy-wide material flows, waste generation, and recycling, while Gao et al. (2020) employed material flow analysis to evaluate regional circular economy development. More broadly, material-flow indicators are also incorporated into the European circular economy monitoring framework, where material use and circular material use are treated as key dimensions of circularity.

The two measures have opposite directional interpretations. Higher values of the Circular Economy Index indicate stronger circular performance, whereas higher MF reflects greater material use and therefore weaker circular performance. Accordingly, a negative coefficient of financial development on MF is economically consistent with a positive effect of financial development on circular economy performance.

As reported in Table 16, financial development has a negative effect on material flow across all six institutional specifications in both country groups. For developed countries, the posterior mean ranges from -0.0125 to -0.0148 , with $P(\beta < 0)$ between 0.9957 and 0.9986, indicating a highly stable negative relationship. For developing countries, the coefficients are smaller, ranging from -0.0035 to -0.0051 , while $P(\beta < 0)$ remains relatively high at 0.9368–0.9751. Overall, Table 17 confirms the robustness of the baseline findings. Because higher MF represents greater material pressure, the consistently negative FD coefficients are economically consistent with the positive FD–CE relationship. The results also reinforce the stronger and more stable role of financial development in developed economies.

Table 16. Robustness test using material flow as an alternative measure of circular economy performance.

Country group	Institutional dimension	Posterior mean of FD	Posterior SD	$P(\beta < 0)$	$P(\beta > 0)$	Monte Carlo error
Developed (30 countries)	CC	-0.0136	0.0031	0.9978	0.0022	0.0001
	GE	-0.0129	0.003	0.9965	0.0035	0.0001
	PS	-0.0142	0.0033	0.9981	0.0019	0.0001
	RL	-0.0131	0.003	0.9972	0.0028	0.0001
	RQ	-0.0148	0.0034	0.9986	0.0014	0.0001
	VA	-0.0125	0.0031	0.9957	0.0043	0.0001
Developing (79 countries)	CC	-0.0042	0.0024	0.9586	0.0414	0.0001
	GE	-0.0038	0.0023	0.9492	0.0508	0.0001
	PS	-0.0047	0.0025	0.9697	0.0303	0.0001
	RL	-0.0044	0.0024	0.9664	0.0336	0.0001
	RQ	-0.0051	0.0026	0.9751	0.0249	0.0001
	VA	-0.0035	0.0023	0.9368	0.0632	0.0001

Source: Authors' calculation.

4.3.6. Robustness to lag structure and global crisis periods

The purpose of this robustness test is to assess whether the estimated effect of financial development is sensitive to temporal specification and major global shocks. Specifically, the baseline model is compared with a one-year lag specification and with models excluding the Global Financial Crisis, the COVID-19 period, and both episodes.

Table 17. Robustness tests by lag structure and sample period.

Country group	Institutional dimension	Baseline	Lag 1 year	Excluding GFC	Excluding COVID	Excluding both
Developed (30 countries)	CC	0.0021	0.0020	0.0022	0.0021	[0.0002]; 0.0023
		[0.0001];	[0.0002];	[0.0002];	0.9998	[0.0002];
		1.0000	0.9997	0.9999		0.9999
	GE	0.0017	0.0016	0.0018	0.0017	[0.0002]; 0.0019
		[0.0002];	[0.0002];	[0.0002];	0.9997	[0.0002];
		1.0000	0.9995	0.9998		0.9999
	PS	0.0023	0.0021	0.0024	0.0022	[0.0002]; 0.0025
		[0.0001];	[0.0002];	[0.0002];	0.9998	[0.0002];
		1.0000	0.9998	0.9999		0.9999
	RL	0.0020	0.0019	0.0021	0.0020	[0.0002]; 0.0022
		[0.0001];	[0.0002];	[0.0002];	0.9997	[0.0002];
		1.0000	0.9996	0.9998		0.9999
	RQ	0.0017	0.0016	0.0018	0.0017	[0.0002]; 0.0019
		[0.0001];	[0.0002];	[0.0002];	0.9996	[0.0002];
		1.0000	0.9994	0.9997		0.9998
	VA	0.0023	0.0022	0.0024	0.0023	[0.0002]; 0.0025
		[0.0001];	[0.0002];	[0.0002];	0.9998	[0.0002];
		1.0000	0.9998	0.9999		0.9999
Developing (79 countries)	CC	−0.0001	−0.0001	−0.0001	−0.0001	[0.0001]; −0.0002
		[0.0001];	[0.0001];	[0.0001];	0.2215	[0.0001];
		0.2051	0.2387	0.1764		0.1086
	GE	0.0001	0.0001	0.0001	0.0001	[0.0001]; 0.0001
		[0.0001];	[0.0001];	[0.0001];	0.7926	[0.0001];
		0.8107	0.7642	0.8365		0.8518
	PS	−0.0005	−0.0004	−0.0005	−0.0004	[0.0001]; −0.0005
		[0.0001];	[0.0001];	[0.0001];	0.0024	[0.0001];
		0.0000	0.0016	0.0003		0.0002
	RL	0.0001	0.0001	0.0001	0.0001	[0.0001]; 0.0001
		[0.0001];	[0.0001];	[0.0001];	0.7117	[0.0001];
		0.6998	0.6745	0.7321		0.7486
	RQ	0.0001	0.0001	0.0001	0.0001	[0.0001]; 0.0001
		[0.0001];	[0.0001];	[0.0001];	0.8315	[0.0001];
		0.8484	0.8019	0.8726		0.8892
	VA	0.0001	0.0001	0.0001	0.0001	[0.0001]; 0.0001
		[0.0001];	[0.0001];	[0.0001];	0.8925	[0.0001];
		0.9066	0.8617	0.9284		0.9416

Source: Authors' calculation.

As reported in Table 17, the results for developed countries remain highly stable across all six institutional specifications. The posterior mean of financial development stays positive after introducing a one-year lag and after excluding the GFC, COVID-19, or both periods, while $P(\beta > 0)$ remains close to one. This indicates that the positive FD–CE relationship in developed economies is not driven by a particular lag structure or crisis period.

For developing countries, the results remain weaker and more heterogeneous. The sign of FD continues to vary across institutional specifications, with negative effects under CC and PS and positive effects under GE, RL, RQ, and VA. However, these patterns are broadly preserved across the alternative temporal specifications. Overall, Table 17 confirms that the main findings are robust to lag structure and major global shocks while preserving the contrast between developed and developing countries.

4.3.7. Prior sensitivity analysis

The purpose of the prior sensitivity analysis is to assess whether the Bayesian estimates of financial development are sensitive to alternative prior assumptions. Specifically, the analysis compares three prior distributions for the FD coefficient: A weak prior $N(0, 10^2)$, which enables relatively high prior uncertainty; a standard prior $N(0, 1)$, used as the benchmark specification; and a shrinkage prior $N(0, 0.5^2)$, which places greater prior mass around zero. This comparison determines whether changes in prior dispersion materially affect the sign, magnitude, or posterior certainty of the FD coefficient.

As reported in Table 18, the developed-country results remain highly stable across all six institutional specifications. The FD coefficient stays positive under all three priors, while the posterior probability of a positive effect remains close to one. Although the shrinkage prior slightly reduces the coefficient magnitude, the substantive inference is unchanged.

For developing countries, the sign of the FD coefficient also remains stable across prior choices, but posterior certainty is generally lower, particularly under CC, GE, and RL. Overall, Table 18 indicates that the main findings are not driven by a specific prior distribution and confirms stronger prior robustness in developed countries than in developing countries.

Table 18. Prior sensitivity analysis of the financial development coefficient.

Country group	Institutional dimension	Weak prior N (0, 10 ²)	Standard prior N (0, 1)	Shrinkage prior N (0, 0.5 ²)
Developed (30 countries)	CC	0.0022 [0.0002]; P ($\beta > 0$) = 0.9999	0.0021 [0.0001]; P ($\beta > 0$) = 1.0000	0.0019 [0.0001]; P ($\beta > 0$) = 0.9998
	GE	0.0018 [0.0003]; P ($\beta > 0$) = 0.9997	0.0017 [0.0002]; P ($\beta > 0$) = 1.0000	0.0015 [0.0002]; P ($\beta > 0$) = 0.9995
	PS	0.0024 [0.0002]; P ($\beta > 0$) = 0.9999	0.0023 [0.0001]; P ($\beta > 0$) = 1.0000	0.0021 [0.0001]; P ($\beta > 0$) = 0.9999
	RL	0.0021 [0.0002]; P ($\beta > 0$) = 0.9998	0.0020 [0.0001]; P ($\beta > 0$) = 1.0000	0.0018 [0.0001]; P ($\beta > 0$) = 0.9997
	RQ	0.0018 [0.0002]; P ($\beta > 0$) = 0.9997	0.0017 [0.0001]; P ($\beta > 0$) = 1.0000	0.0015 [0.0001]; P ($\beta > 0$) = 0.9995
	VA	0.0024 [0.0002]; P ($\beta > 0$) = 0.9999	0.0023 [0.0001]; P ($\beta > 0$) = 1.0000	0.0021 [0.0001]; P ($\beta > 0$) = 0.9998
Developing (79 countries)	CC	-0.00012 [0.00015]; P ($\beta < 0$) = 0.7826	-0.0001 [0.0001]; P ($\beta < 0$) = 0.7949	-0.00008 [0.00009]; P ($\beta < 0$) = 0.7680
	GE	0.00012 [0.00015]; P ($\beta > 0$) = 0.7884	0.0001 [0.0001]; P ($\beta > 0$) = 0.8107	0.00008 [0.00009]; P ($\beta > 0$) = 0.7862
	PS	-0.00053 [0.00015]; P ($\beta < 0$) = 0.9995	-0.0005 [0.0001]; P ($\beta < 0$) = 1.0000	-0.00044 [0.00009]; P ($\beta < 0$) = 0.9993
	RL	0.00011 [0.00015]; P ($\beta > 0$) = 0.6815	0.0001 [0.0001]; P ($\beta > 0$) = 0.6998	0.00007 [0.00009]; P ($\beta > 0$) = 0.6734
	RQ	0.00012 [0.00015]; P ($\beta > 0$) = 0.8276	0.0001 [0.0001]; P ($\beta > 0$) = 0.8484	0.00008 [0.00009]; P ($\beta > 0$) = 0.8217
	VA	0.00012 [0.00015]; P ($\beta > 0$) = 0.8872	0.0001 [0.0001]; P ($\beta > 0$) = 0.9066	0.00008 [0.00009]; P ($\beta > 0$) = 0.8795

Source: Authors' calculation

4.3.8. Comparison of Bayesian and conventional panel-data estimators

Table 19 compares the FD coefficient across Bayesian and conventional estimators. In developed countries, FEM, REM, and Two-way FEM produce positive coefficients of about 0.001, although country-clustered p-values (0.160–0.195) indicate weaker frequentist precision. In contrast, the

Bayesian estimates remain consistently positive across all six institutional-quality specifications, with posterior means ranging from 0.0017 to 0.0023 and $P(\beta_{FD} > 0) = 1.000$. For developing countries, Pooled OLS yields a positive coefficient of 0.002, but the estimate falls to approximately zero under FEM, REM, and Two-way FEM; the Two-way FEM clustered p-value reaches 0.730. Bayesian results similarly show weak and heterogeneous evidence, with posterior means ranging from -0.0005 to 0.0001 . Overall, the comparison indicates a more stable positive relationship between financial development and circular economy performance in developed countries, while the relationship remains considerably weaker and less certain in developing countries.

Table 20 shows significant heteroskedasticity, autocorrelation, and non-normality in both country groups, with all diagnostic tests yielding $p < 0.001$. These results indicate limitations in conventional inference. Therefore, Bayesian regression is retained as the principal estimation framework because it provides full posterior distributions, credible intervals, and direct probabilistic inference, while conventional panel estimators are used as complementary benchmarks.

Table 19. Comparison of the financial development coefficient across alternative estimators.

Country group	Estimator	FD coefficient	Statistical/Posterior evidence
Developed	Pooled OLS	0.0000	Clustered p = 0.819
	FEM	0.0010	Clustered p = 0.191
	REM	0.0010	Clustered p = 0.195
	Two-way FEM	0.0010	Clustered p = 0.160
	Bayesian	0.0017–0.0023	$P(\beta_{FD} > 0) = 1.000$ across all six specifications
Developing	Pooled OLS	0.0020	Clustered p = 0.001
	FEM	0.0000	Clustered p = 0.114
	REM	0.0000	Clustered p = 0.088
	Two-way FEM	0.0000	Clustered p = 0.730
	Bayesian	-0.0005 to 0.0001	$P(\beta_{FD} > 0) = 0.0000$ – 0.9066 across six specifications

Source: Authors' calculation.

Table 20. Panel-data diagnostic tests.

Country group	Heteroskedasticity p-value	Autocorrelation p-value	Jarque–Bera p-value	Heteroskedasticity	Autocorrelation
Developed	< 0.001	< 0.001	< 0.001	Yes	Yes
Developing	< 0.001	< 0.001	< 0.001	Yes	Yes

Source: Authors' calculation.

4.4. Discussion

The Bayesian results show that financial development does not affect circular economy performance uniformly across country groups. In developed countries, the effect of financial development is positive, stable, and supported by high posterior probabilities. This finding is consistent with financial intermediation theory, which emphasizes the role of the financial system in mobilizing savings, allocating capital, monitoring investment, and managing risk (Levine, 1997; Beck et al., 2000). In the circular economy context, these functions can reduce financing constraints for clean technologies, renewable energy, recycling, remanufacturing, and other resource-efficient activities. The result is also consistent with the Ellen MacArthur Foundation (2015), which views finance as an important enabling mechanism for circular business models.

The evidence for developing countries is weaker and more heterogeneous. Financial development does not consistently translate into higher circular economy performance, suggesting that an expansion of credit alone is insufficient to support circular transition. One explanation is that financial resources in developing economies may remain concentrated in conventional sectors such as construction, heavy industry, mining, and fossil-energy-based production. Under these conditions, deeper financial systems can expand economic activity without necessarily reducing material pressure or improving resource efficiency. This interpretation is consistent with Chen et al. (2026), who showed that private-sector credit can be associated with higher municipal waste generation, and with Fang et al. (2024), who noted that investment directed toward circular economy activities remains relatively limited.

The difference between developed and developing economies therefore appears to reflect the quality of capital allocation rather than financial depth alone. In developed countries, stronger technological capabilities, more mature environmental infrastructure, and greater availability of sustainable investment opportunities may enable financial development to support circular activities more effectively. In developing countries, similar increases in financial depth may produce weaker circular outcomes when the structure of production remains resource intensive. This helps explain why the same financial indicator can generate different environmental and resource-use consequences across levels of development.

The findings also reinforce the importance of measuring the circular economy as a multidimensional phenomenon. Recycling rates, waste treatment, or individual energy indicators capture only particular aspects of circularity. The composite index developed in this study combines

carbon efficiency, energy efficiency, energy transition, and material pressure, thereby capturing broader changes in the relationship between economic production, energy use, emissions, and material dependence. This approach is consistent with multidimensional circular economy measurement in Geng et al. (2012), Elia et al. (2017), Moraga et al. (2019), Mayer et al. (2019), Haas et al. (2020), Claudio-Quiroga and Poza (2024), and Emami et al. (2025).

Two broader conclusions follow. First, financial development should not be interpreted as an automatic driver of circularity. Its contribution depends on whether financial resources are directed toward activities that reduce resource intensity and support cleaner production. Second, the finance-circular economy relationship is structurally heterogeneous. The stronger and more stable effect observed in developed economies suggests that financial development becomes more supportive of circular transition when complementary technological, institutional, and productive capacities are already in place.

The results also help distinguish finance for the circular economy from green finance more broadly. Green finance commonly emphasizes renewable energy, low-carbon infrastructure, and emission reduction. Circular economy finance has a wider material dimension, including product durability, reuse, repair, remanufacturing, reverse logistics, high-quality recycling, and business models that reduce demand for primary materials. This distinction matters because improvements in carbon performance do not necessarily imply greater circularity if material throughput remains high. The findings therefore suggest that the financial dimension of circular transition should be evaluated not only through its contribution to decarbonization, but also through its ability to reduce material dependence and extend the economic value of resources.

5. Conclusions

5.1. Conclusions

In this study, we pursue two objectives: To construct a macro level circular economy index and to examine the impact of financial development on the circular economy across developed and developing countries. The results show that both objectives are linked by a consistent logic. The circular economy must first be measured broadly enough; only then can the role of finance in circular transition be meaningfully assessed.

In terms of measurement, we construct the circular economy index from four dimensions: carbon efficiency, energy efficiency, energy transition, and material pressure. The KMO value is 0.7620, and the Bartlett test is statistically significant, indicating that the data are suitable for PCA. The first principal component has an eigenvalue of 2.3149 and explains 57.87 percent of total variance, and is therefore used as the composite circular economy index. All four indicators have positive loadings on PC1, with energy transition and energy efficiency making the largest contributions. This indicates that energy is a key axis of macro level circular transition, while carbon reduction and material pressure reduction remain indispensable dimensions.

The comparison results show that developed countries have an average circular economy index of 0.864, which is substantially higher than the 0.413 recorded for developing countries. Levene, Welch t, and Mann-Whitney U tests all confirm that this difference is statistically significant. Circular

transition is therefore uneven across country groups and is shaped by technology, energy systems, environmental infrastructure, and development capacity.

Regarding financial development, the Bayesian regression results show that financial development has a positive and very stable effect on the circular economy in developed countries. The coefficient is positive in all six models, with a posterior probability of a positive effect equal to 1.0000. In developing countries, the effect is smaller and less stable. Finance can promote the circular economy when the financial system allocates capital to clean technologies, renewable energy, recycling, remanufacturing, and circular business models. In developing economies, however, financial expansion may not produce circular outcomes if capital continues to serve resource intensive sectors or linear growth patterns.

5.2. Theoretical implications

This article has three theoretical implications. First, it contributes to the circular economy measurement literature by proposing a macro level index based on multiple dimensions. This approach helps address the limitations of single indicators that focus mainly on recycling, waste, or resource productivity. The circular economy is treated as a system in which carbon, energy, and material flows jointly determine the degree of transition.

Second, we extend financial intermediation theory to the circular economy context. Finance supports not only economic growth through capital mobilization and allocation; it can also shape the growth model that an economy follows. If capital flows into clean technologies and circular activities, financial development can support transition. If capital continues to flow into resource intensive industries, finance may reinforce the linear model. The quality of capital allocation is therefore as important as the size of finance.

Third, the different results between developed and developing countries show that the effect of finance should not be assumed homogeneous. The same financial development indicator may reflect different realities across groups. In developed countries, it may be associated with green finance, deeper capital markets, and better risk management. In developing countries, it may mainly reflect general credit expansion, not necessarily finance for circular activities. This point deserves attention in empirical studies on finance and sustainable development.

5.3. Policy implications

5.3.1. Improving circular economy measurement and monitoring systems

Countries should build multidimensional circular economy data systems. Indicator sets should include carbon emissions, energy efficiency, renewable energy share, material pressure, waste, secondary materials, and resource productivity. Without reliable data, circular economy policy can become a slogan or be reduced to end-of-life recycling. Developing countries should first standardize material flow, energy, and emissions data to create a sound basis for policy monitoring.

5.3.2. Orienting financial development toward the circular economy

The results suggest that financial development is more strongly associated with circular economy performance in developed countries. The policy implication is therefore not simply to expand credit, but to improve how financial resources are allocated. Greater attention should be given to directing finance toward activities that improve energy efficiency, increase the use of renewable energy, reduce waste, extend product life cycles, and lower emissions. Clear evaluation and monitoring criteria are also needed to ensure that financial resources genuinely support circular economy objectives.

5.3.3. Implications for developed countries

For developed countries, the main challenge is not the lack of finance, but the quality of capital allocation. These countries should move from general green finance toward specialized circular finance. This includes bonds or loans for eco design, repair, reuse, remanufacturing, reverse logistics, and product as service models. Disclosure on material flows, product life cycles, and resource efficiency should also be expanded so that investors can properly evaluate the circular benefits of projects.

5.3.4. Implications for developing countries

For developing countries, policy should focus on reducing capital and technology barriers. Governments should help firms access long term capital for machinery renewal, energy efficiency improvement, renewable energy, recycling, and waste treatment. Furthermore, capital flows into resource intensive or high emission sectors should be limited. Combining public capital, private capital, and international finance can help reduce risks for circular projects at the early stage.

For Vietnam, the results suggest three policy directions. First, Vietnam should improve data systems on emissions, energy, material flows, recycling, and secondary material use to monitor circular economy progress more quantitatively. Second, green finance instruments should be developed to support firms investing in energy saving technologies, recycling, remanufacturing, and waste treatment. Third, circular economy policy should be linked to industrial strategy and energy transition rather than focusing only on end-of-life waste management. This is important because Vietnam is industrializing, and growth remains closely tied to energy consumption and material inputs.

5.3.5. Macroeconomic stability and digital transformation as supports for circular transition

The control variables suggest that the circular economy is affected by the macroeconomic environment. High inflation can increase the cost of capital and reduce long term investment in circular technologies. Urbanization can support waste management and recycling infrastructure if it is well planned, but it can also raise material pressure if urban governance is weak. Digital technology and Internet use can support traceability, supply chain optimization, and emission monitoring, but they are effective only when connected to firm capacity and reliable environmental data.

5.4. *Research limitations*

This study has several limitations. First, the circular economy index is constructed from four macro dimensions and therefore cannot fully capture all circular practices at the firm, product, or household level. Practices such as eco design, repair, reuse, remanufacturing, sustainable consumption, and circular business models are not directly included because of cross country data limitations.

Second, the data are collected from internationally comparable sources, but statistical quality may differ across countries. Some developing countries have incomplete environmental, energy, and material data, which may affect index precision. Third, PCA helps reduce subjectivity in weighting, but the resulting weights depend on the correlation structure of the dataset, the country sample, and the study period.

Fourth, financial development is measured by domestic credit to the private sector as a share of GDP. This is a common measure, but it does not fully capture green finance quality or the extent to which capital actually flows into circular activities. The financial development results should therefore be understood as the effect of financial depth in general, not the separate effect of green finance or circular finance.

Another limitation is that we use only PC1 to construct the circular economy index. PC2 has an eigenvalue of 0.9706, close to the Kaiser threshold of 1.0, and explains an additional 24.27 percent of variance. This suggests that PC2 may contain additional information about differences between material pressure, carbon efficiency, and energy factors. However, to maintain a simple, consistent, and internationally comparable main index, the study retains PC1 as the composite measure. In future studies, researchers could test multi component indices or sub-indices based on PC2.

5.5. *Future research directions*

Researchers may proceed in three directions. First, firm-level or sector-level indicators can be incorporated when data permit to clarify the mechanisms of circular transition in specific industries. Second, green finance, green bonds, green credit, or sustainable investment measures can be used to test the transmission channel from finance to the circular economy more directly. Researchers should also distinguish financial institutions and financial markets, as these dimensions are not explicitly examined in this study. Third, the roles of institutional quality, environmental regulation, or climate policy can be explored as separate extensions to assess the conditions that shape the impact of financial development on the circular economy.

Author contributions

Le Quoc Dinh: Conceptualization, methodology, data curation, formal analysis, investigation, visualization, writing—original draft, writing—review and editing, and project administration.

Tran Thi Kim Oanh: Supervision and writing—review and editing.

Both authors have read and approved the final version of the manuscript.

Use of AI tools declaration

Artificial intelligence tools were used solely to correct spelling and grammatical errors and to improve language clarity. They were not used in the research design, data analysis, interpretation of the results, or preparation of the study's substantive content. The authors take full responsibility for the final manuscript.

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Conflict of interest

The authors declare that they have no conflicts of interest.

Data availability statement

The data used in this study will be made available by the corresponding author upon reasonable request.

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