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STRUCTURAL DETERMINANTS OF PATENT ACTIVITY: A PANEL ANALYSIS OF INNOVATION DRIVERS ACROSS INCOME GROUPS

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ABSTRACT

This study examines the structural determinants of patent activity across 65 countries from 2010 to 2023, comparing high-income, upper-middle-income, and lower-middle/low-income economies, with an additional pooled estimation serving as a global benchmark. Guided by Endogenous Growth, Schumpeterian, and Institutional–Systems perspectives, the analysis operationalises nine determinant categories using 44 proxy indicators. It estimates patent counts using a Poisson Pseudo-Maximum Likelihood model with country- and year-fixed effects. The results show that no single determinant and its proxy indicator operate uniformly across all income groups. Tax Revenue and Infrastructure availability are the only proxies that are statistically significant across all three income categories, but both display directionally heterogeneous effects, underscoring strong income-contingent dynamics. Education-related proxies show differentiated roles: Knowledge Workers are significant in high- and upper-middle-income economies, while Tertiary Enrolment is significant in upper-middle- and lower-income contexts. Access to Finance plays a significant role in upper-middle- and lower-income economies, with particularly strong relevance in lower-income contexts. Other economic, regulatory, innovation, and institutional factors operate in income-specific or income-pair configurations rather than globally consistent patterns. The pooled model reinforces these findings by identifying which income-specific determinants also retain relevance at the global level. Overall, the evidence demonstrates that patent activity is shaped by income-dependent combinations of fiscal structure, infrastructure conditions, human capital composition, and financial capacity, emphasizing the limitations of uniform innovation policy approaches across heterogeneous economies.

KEYWORDS: Patent Activity; Innovation Systems; Poisson Pseudo-Maximum Likelihood (PPML-FE); Institutional Quality; Human Capital; Cross-Country Panel Analysis.

1. INTRODUCTION

Patent activity remains a central indicator of how effectively nations convert knowledge into technological and economic progress. Global filings have surged over the past two decades, particularly in digital and research-intensive sectors. (Santa Rita et al., 2023; WIPO, 2024). However, this growth is highly uneven: high-income economies, including the United States, Japan, and even upper-middle-income country China, continue to dominate patent registrations, while many developing countries register only modest gains despite advances in education and connectivity. These disparities underscore how institutional and systemic conditions such as governance quality, innovation financing, and absorptive capacity shape inventive performance (Castellacci et al., 2022).

Recent studies have moved beyond single-indicator and single-country analyses toward multidimensional frameworks that integrate institutional, financial, and digital determinants of innovation (Ferreira et al., 2024). Nevertheless, several high-quality studies continue to highlight methodological limitations in the existing literature. Liu (2024), found that much patent quality research lacks reproducibility and applies inconsistent indicators, while Todorov et al. (2024), criticized traditional innovation system approaches as too limited to capture broader dynamics. Similarly, Stundziene et al. (2024) and Todorov et al. (2024), demonstrated that single-perspective indicators fail to represent the complex, longitudinal nature of innovation outcomes. To address these shortcomings, this study adopts a comprehensive, cross-country, longitudinal design to examine how institutional, financial, and digital factors jointly shape patent activity across income groups.

This study addresses those limitations by using a balanced panel of 65 countries from 2010 to 2023 and modelling patent activity as an outcome of 9 determinants, represented by 44 proxy indicators. The estimations employ a Poisson Pseudo–Maximum Likelihood model with two-way fixed effects (country and year) to account for unobserved heterogeneity and time-specific shocks. The design also stratifies the sample into all-income, high-income, upper-middle, and lower-middle/low panels, enabling consistent comparison of common and context-specific influences on patenting outcomes. By applying a unified PPML-FE framework across income groups and over time, the study provides one of the first systematic cross-group assessments of how structural and institutional determinants jointly shape patent activity on a global scale.

The study draws on three complementary theoretical perspectives to explain how economic, institutional, and innovation dynamics influence patent activity across countries. Endogenous Growth Theory links knowledge accumulation, R&D investment, and technological progress to long-term innovation and productivity. Schumpeterian Innovation Theory emphasizes creative destruction, where new technologies and entrepreneurial competition drive structural change. Institutional and Systems Theory underscores the role of governance quality, regulatory efficiency, and networked innovation systems connecting firms, academia, and the state. Together, these perspectives position patent activity as a systemic outcome of interacting economic and institutional conditions, providing a theoretical basis for examining diverse determinants across income-differentiated innovation systems.

The main objective of this study is to examine the determinants of patent registration across countries, both within distinct income groups and in the pooled global model. Using a balanced panel of sixty-five countries from 2010 to 2023, the analysis investigates how different determinants identified in the literature shape patent outcomes over time.

Accordingly, the study addresses three core questions:

1. Which determinants significantly influence patent registration within high-, upper-middle-, and lower-middle/low-income groups?
2. Which of these determinants remain consistent or differ when analysed under the pooled all-income model?
3. Do these relationships remain stable once differences across countries and years are controlled for?

This study contributes to the literature by combining theoretical breadth with empirical rigor. It integrates a diverse set of determinants within a unified analytical framework to explain variations in patent activity across income-differentiated country groups and in the pooled global model. The comparative design enables a consistent assessment both within and across income groups, revealing how the influence of specific determinants varies across innovation systems while maintaining methodological comparability through a unified estimation strategy. Beyond its methodological contribution, the study also holds practical relevance, offering a foundation for evidence-based policy and providing countries with a benchmark for evaluating their patent systems and identifying structural priorities to strengthen patent performance.

2. LITERATURE REVIEW

2.1. Overview of Patent Determinant Studies

The literature on patent determinants has gradually expanded. Early studies tended to isolate variables, while recent research increasingly applies multidimensional and longitudinal approaches that reflect the systemic character of innovation. Scholars now integrate broader institutional, financial, and legal determinants to capture complex and dynamic relationships. Analyses of cross-border patenting further emphasize globalization and technology-transfer dynamics, reinforcing the shift toward integrated models sensitive to structural heterogeneity among countries (Yu et al., 2025).

2.2. Linking Determinants to Theoretical Perspectives

Patent activity reflects how economies combine knowledge creation, institutional support, and financial capacity to generate innovation. Endogenous Growth Theory (Grossman & Helpman, 1993; Lucas, 1988; Romer, 1990) Explains the role of macroeconomic scale, investment, and education in fostering human capital and sustaining knowledge accumulation. Schumpeterian Innovation Theory (Aghion & Howitt, 1992; Schumpeter, 1934, 1942), focuses on creative destruction, industrial competition, and R&D-driven technological progress. Institutional and Systems Theory (Edquist, 1997; Freeman, 1987; Lundvall, 1992) highlights governance quality, regulatory efficiency, and infrastructure as structural conditions that enable the diffusion of innovation. Together, these frameworks inform the nine determinants analysed in this study, clarifying how distinct yet interdependent mechanisms influence patent performance across income-based contexts. Table 1 lists the theoretical determinants and associated theories used in this study.

Table 1: Theoretical Perspectives and Associated Determinants.

Theoretical Perspective	Associated Determinants
Endogenous Growth Theory	Economic performance & market size (ECON), investment & financial environment (INVF – *primary*), and education & human capital (EDUC).
Schumpeterian Innovation Theory	Innovation & R&D (INRD), and intellectual property & innovation outputs (IPIO).
Institutional and Systems Theory	Infrastructure & digital connectivity (INFR), regulatory & business environment (REGB), legal & institutional framework (LEGL), property and infrastructure development (PROP), and investment & financial environment (INVF – *secondary*).

2.2.1. Economic Performance and Market Size (ECON)

According to endogenous growth theory, the scale and performance of an economy influence its innovation capacity by enabling increasing returns to knowledge accumulation, effective R&D investment, and larger markets for commercialization (Etro, 2023). Core macroeconomic indicators like GDP per capita, GDP growth, gross capital formation, trade intensity, exports, and industrial activity serve as proxies for market size, absorptive capacity, and investment dynamics. Empirical evidence affirms several of these linkages. Rubilar-Torrealba et al. (2022), show that higher GDP per capita and greater trade openness are significantly associated with increased patent activity across 99 countries. Etro (2023), further confirms that growth is sustained through R&D investments under increasing returns, with policy-sensitive channels such as capital formation playing a key role. A recent panel study published by Gonzales (2023), also finds that gross capital formation per capita is a statistically significant predictor of patent-related innovation. While theoretical frameworks emphasize the role of industrial activity in fostering innovation via production intensity, clustering, and spillovers, robust empirical studies linking industrial activity to patent output across countries remain limited. These findings underscore that GDP level, growth, capital investment, and openness are key economic enablers of innovation, as predicted by endogenous growth theory.

Although some ECON proxies, such as capital formation, intersect with financial factors, their inclusion here captures macroeconomic scale rather than financial facilitation, consistent with Endogenous Growth Theory and supported by acceptable VIF and Cronbach α values.

2.2.2. *Investment and Financial Environment (INVF)*

Endogenous Growth Theory and Innovation Systems Theory both emphasize that a country's investment and financial environment significantly shape its capacity for sustained technological advancement. Endogenous models posit that investments in R&D, financial infrastructure, and innovation systems enable long-run growth by enhancing knowledge creation and diffusion (Etro, 2023). Similarly, the innovation systems perspective highlights how institutional arrangements, including financial and investment policy frameworks, influence national innovation capabilities (Archibugi & Lundvall, 2002). Empirical research supports these theoretical underpinnings: Sánchez-Sellero & Bataineh (2024) show that foreign direct investment enhances firms' innovation performance by strengthening their absorptive capacity. Tax incentives are also critical Y. Li et al. (2023), find that R&D Tax policy significantly improves innovation outcomes by easing financing constraints, while Feng (2024), highlights the positive role of cross-border Tax support for R&D. Although direct panel-based evidence linking domestic credit to patenting remains limited, financial depth and credit access are acknowledged indicators of a robust investment environment. Pal et al. (2025), show that access to alternative credit (FinTech) and institutional quality significantly affect innovation across 89 countries. Although FDI and capital formation both relate to capital flows, they are treated as distinct within INVF and ECON to separate macroeconomic performance from financial facilitation. Collectively, these findings underscore the importance of financial openness, Tax policy, and credit systems in sustaining innovation-led patent performance, in line with both theoretical frameworks.

2.2.3. *Innovation and R&D (INRD)*

Grounded in Schumpeterian Innovation Theory, empirical evidence underscores how R&D intensity and innovation proxies drive patent activity across economies. Using R&D expenditure as a central indicator, Tajaddini & Gholipour (2020), found that higher R&D expenditure significantly increases patent applications in OECD countries, confirming the Schumpeterian link between innovation and capital accumulation. Similarly, X. Yang et al. (2025), demonstrated that scientific and technical journal articles and university knowledge creation enhance patent intensity in Chinese high-tech firms. Moreover, Hu et al. (2024), showed that high-technology exports amplify R&D efficiency in export-led innovation systems, particularly in upper-middle-income economies. Collectively, these studies affirm that while developed nations capitalize on STA and HTE through robust innovation ecosystems, developing economies still face structural constraints that limit the full returns of R&D-led patenting.

2.2.4. *Education and Human Capital (EDUC)*

Anchored in endogenous growth theory, the accumulation of human capital through education is considered central to long-run technological progress and patent-based innovation (Eriksson et al., 2023; Lucas, 1988; Romer, 1990). The theory posits that education enhances a country's absorptive capacity, drives knowledge creation, and sustains innovation through increasing returns. Recent empirical evidence reinforces this view. W. Li et al. (2024), show that the structure of human capital significantly improves innovation efficiency and patent outputs across countries. Using a panel VAR model, Bambi and Pea-Bambi & Pea-Assounga (2025), find that increases in tertiary enrollment and human capital formation lead to higher technological innovation and patent activity in developing countries. Mabrouki (2023), identifies a long-term cointegration among government education expenditure, the human capital index, and patent growth across Scandinavian economies. Y. Huang et al. (2024) further note that human capital mismatches in high-tech firms hinder innovation outcomes, underscoring the quality of education and skill alignment. Collectively, these studies validate the relevance of GED, TER, HCI, STEM graduates (STG), and knowledge workers (KWS) as indicators of the EDUC determinant that influences national patenting performance.

2.2.5. *Infrastructure and Digital Connectivity (INFR)*

Rooted in Institutional and Systems Theory, innovation emerges from system-wide interactions shaped by institutional capacities and infrastructure. Within this framework, both energy infrastructure, proxied by access to electricity, and digital connectivity, measured by individuals' internet use, fixed broadband subscriptions, mobile subscriptions, and ICT access, are seen as foundational enablers of innovation.

Empirical studies support this: Ur Rehman & Islam (2023), show that energy infrastructure significantly increases total factor productivity in 67 upper- and middle-income countries, with more substantial innovation spillovers in upper-middle-income economies.

Cotter (2021) further finds that energy and telecom investments reduce power disruptions and enhance innovation at the firm level in developing nations. In digital domains, Gomes & Lopes (2022), demonstrate that ICT access, particularly mobile and broadband connectivity, significantly boosts entrepreneurial activity.

Complementing these findings, composite indicators like the Infrastructure Index (INF) and Productive Capacity Index (PCI) capture broader readiness. These proxies collectively operationalize the institutional dimension of IST by reflecting how physical and digital infrastructure co-support innovation ecosystems.

2.2.6. Regulatory and Business Environment (REGB)

Within the framework of institutional and systems theory, the regulatory and business environment (REGB) serves as a core institutional layer that influences innovation through legal, fiscal, and market-enabling mechanisms. Recent empirical research supports this multidimensional view. Zhang and Jiang (2024), demonstrate that investment deregulation in China significantly enhances private firms' patent output via preemptive innovation mechanisms.

In parallel, Chen et al. (2025), show that a favourable tax business environment fosters higher levels of regional innovation, emphasizing the tax policy's regulatory role. While specific studies on the time and cost to start a business remain limited, this dimension is integral to broader ease-of-doing-business reforms that reduce entry barriers to entrepreneurial activity. Crucially, minority investor protections are increasingly recognized as catalysts for innovation: Wang and Li (2023) find that shareholder activism is positively associated with future innovation performance in Chinese firms; F. Huang et al. (2023), reveal that minority shareholder safeguards enhance investment efficiency, especially in non-state enterprises; and Corvello et al. (2023), demonstrate that owners' minority status significantly affects digital patenting activities. Bahlous-Boldi (2022), links minority rights to increased access to credit. Because REGB proxies span taxation, entry barriers, and investor rights, their multidimensional scope reflects the composite institutional mechanisms emphasized in IST.

2.2.7. Legal and Institutional Framework (LEGL)

Institutional and Systems Theory underscores that robust legal and institutional frameworks are essential to sustaining innovation ecosystems by shaping governance quality, reducing uncertainty, and promoting technological progress. Empirical evidence consistently shows that institutional quality and governance indicators, such as the rule of law, government effectiveness, political stability, and corruption control, significantly influence national innovation performance. Arshed et al. (2022), identified a non-linear, inverted-U-shaped relationship between institutional development and innovation, indicating that excessive regulation can constrain innovative capacity. Qamruzzaman et al. (2021), further revealed that regulatory quality and corruption control enhance innovation outputs through improved capital flows and policy stability. Plata et al. (2021), showed that institutional heterogeneity shapes entrepreneurial networking within innovation ecosystems, while Reverte (2022), confirmed that strong governance and regulatory quality enable sustainable innovation aligned with development goals. Collectively, these studies affirm that effective legal and institutional structures underpin the credibility, inclusiveness, and resilience of patent-driven innovation systems.

2.2.8. Innovation Outputs and Intellectual Property (IPIO)

Grounded in Schumpeterian Innovation Theory, innovation outputs and intellectual property reflect a cyclical process of technological competition and creative destruction that drives patent growth. Empirical evidence confirms that patent protection and innovation activity are dynamically intertwined within this framework (Chu et al., 2021). At the systemic level, the Global Innovation Index (GII) serves as a robust indicator of innovation performance and patent output, with countries demonstrating varying efficiency in converting innovation inputs into tangible outputs (Erdin & Çağlar, 2023). Beyond national systems, firm- and sector-level characteristics further moderate innovation outcomes. Collaborative innovation and firm size, in particular, have been shown to significantly influence innovation performance, with supply-chain collaborations exerting more potent effects than academic partnerships (Xie et al., 2023). Together, these findings underscore that innovation outputs function as the operational link between institutional systems and patent-based growth, validating the Schumpeterian premise that competition and institutional efficiency jointly sustain technological advancement.

2.2.9. Property and Infrastructure Development (PROP)

Institutional and Systems Theory underscores that institutional efficiency and legal infrastructure shape the systemic capacity for innovation by minimizing uncertainty and transaction costs. Within this framework, efficient property registration, as reflected in indicators such as Registering Property – Time and Registering Property – Procedures, serves as a tangible expression of institutional quality. Usman et al. (2021), demonstrate that streamlined legal institutions and more vigorous enforcement of property rights significantly enhance corporate innovation, especially in developing economies where procedural inefficiencies often deter investment. Complementing this, Bian et al. (2025) find that predictable property-rights systems foster technology transfer. While PROP draws narrowly on registration indicators, it captures the procedural efficiency dimension of institutional systems consistent with IST.

Table 2 summarizes the operationalization of all theoretical determinants across the three theories used in this study. Details about the proxies, measurement units, and data sources are listed in Appendix Table A1.

Table 2: Summary of Patent Determinants and Proxies.

Determinant	Associated Proxies
ECON (Economic Performance and Market Size)	GDP per capita (GPC), GDP growth (GGW), Gross Capital Formation (GCF). Trade Intensity (TRD), Exports (EXP), Industrial Activity (IND)
INVF (Investment and Financial Environment)	Foreign Direct Investment (FDI), Tax Revenue (TAX), Domestic Credit (DCR), Access to Finance (ATF), Getting Credit (SGC)
INRD (Innovation and R&D)	R&D Expenditure (RDX), Scientific and Technical Journal Articles (STA), High-Technology Exports (HTE), Knowledge Creation (KNC)
EDUC (Education and Human Capital)	Government Education Expenditure (GED), Gross Enrollment Ratio, Tertiary (TER), Human Capital and Research Index (HCI), STEM Graduates (STG), Knowledge Workers (KWS)
INFR (Infrastructure and Digital Connectivity)	Access to Electricity (ELE), Individuals Using the Internet (INT), Fixed Broadband Subscriptions (FSB), Mobile Cellular Subscriptions (MOB), Infrastructure Index (INF), ICT Access (ICT), Productive Capacity Index (PCI)
REGB (Regulatory and Business Environment)	Ease of Doing Business (EBD), Starting a Business (SBS), Paying Tax (SPT), Cost of Business Start-up Procedures (CST), Time Required to Start a Business (TRT), Business Environment Index (BEV), Protecting Minority Investors (PMI)
LEGL (Legal and Institutional Framework)	Government Effectiveness (GEV), Rule of Law (ROL), Political Stability and Absence of Violence (PSV), Regulatory Quality (RUQ), Control of Corruption (COC)
IPIO (Intellectual Property and Innovation Outputs)	Global Innovation Index (GII), Creative Output Index (COI), Innovation Efficiency Ratio (IER)
PROP (Property and Infrastructure Development)	Registering Property – Time (RPT), Registering Property – Procedures (RPP)

2.3. Summary and Conceptual Linkage to Methodology

The literature demonstrates that economic, institutional, and innovation-related determinants shape patent activity.

Grounded in Endogenous Growth Theory, Schumpeterian Innovation Theory, and Institutional and Systems Theory, these nine determinants explain how countries transform knowledge and resources into patentable outputs. Each determinant operates through distinct yet complementary channels ranging from macroeconomic performance and finance to legal, infrastructural, and educational capacities.

While prior studies explored individual determinants in isolation, few have integrated them within a unified empirical framework.

Table 2 consolidates these determinants and proxies, providing a comprehensive basis for analysis.

This theoretical synthesis directly informs the econometric model developed in the following chapter.

2.4. Conceptual Framework

Figure 1 presents the conceptual framework that aligns the three theoretical foundations, Endogenous Growth, Schumpeterian, and Institutional & Systems Theory, with nine determinants and forty-four proxies.

It illustrates their complementary interaction in shaping patent activity across income groups, linking conceptual synthesis to empirical design.

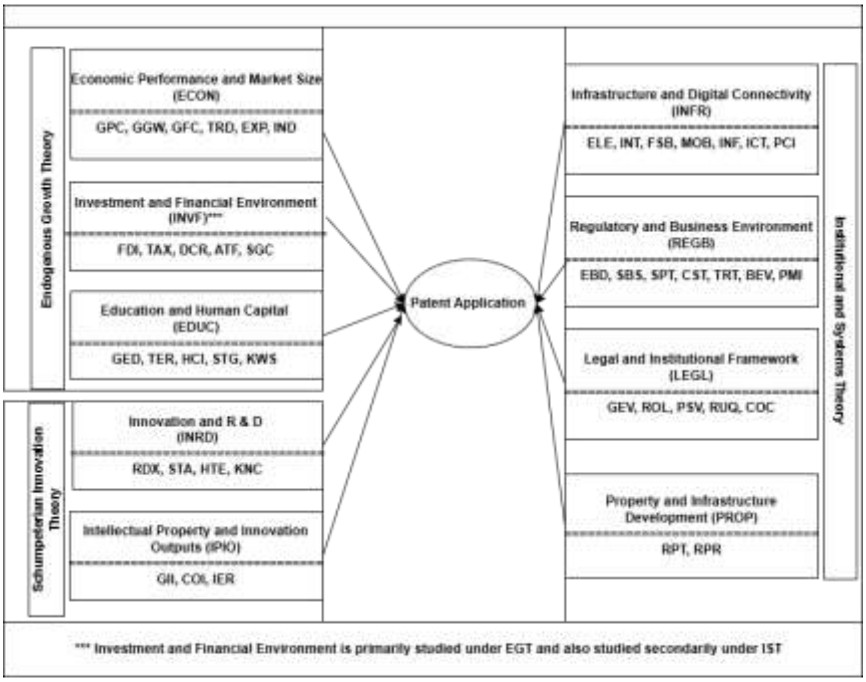

Figure 1: Conceptual Framework

3. METHODOLOGY

Research Design and Framework Alignment

The study employs a quantitative panel design to examine how macro-level determinants influence patent activity across 65 countries between 2010 and 2023. Recent cross-national research demonstrates that panel-data methods combining temporal and cross-sectional variation provide a robust framework for assessing within-country dynamics and cross-country differences in innovative performance (Yoruk et al., 2023). Countries are grouped into four panels following the World Bank's 2023 income classification: a Pooled (All) income panel representing the full sample and three subsets: High Upper-Middle-, and Lower-Middle/Low-Income derived from it. This structure allows consistent estimation and comparison across development levels (World Bank, 2023).

The unit of analysis is the country-year observation, with patent applications serving as the dependent variable representing inventive output. Explanatory variables are organized into nine determinants and 44 proxies as summarized in Table 2. Estimation relies on Poisson Pseudo-Maximum Likelihood with two-way fixed effects for country and year to control for unobserved heterogeneity and standard shocks (Santos Silva & Tenreyro, 2022).

Each diagnostic and estimation step operationalizes the theoretical linkages outlined earlier, enabling empirical testing of growth-, innovation-, and institution-based determinants within a unified framework.

3.1. Data Collection and Country Selection

Annual data (2010–2023) were compiled from various renowned public sources (Appendix Table A1). Countries were included if at least 75% of observations across 44 proxies were available and if they adequately represented income diversity. Minor missing values were imputed using spline smoothing and forward/backward interpolation, consistent with evidence that spline-based methods effectively preserve nonlinear temporal patterns in longitudinal datasets (Falini et al., 2022). Because of limited low-income coverage, low- and lower-middle-income economies were merged as a standard practice in global innovation studies. All proxies, details, units, and sources appear in Appendix Table A1. The list of countries by income group appears in Appendix Table A2.

3.2. Data Preparation and Transformation

After assembly, the dataset was cleaned for consistency: duplicates were removed, years were aligned, and identifiers were standardized. When indicators overlapped, the most complete series was retained.

All proxies were standardized using z-scores to remove scale effects and ensure comparability. For each proxy X_{it}:

$$Z_{it} = \frac{X_{it} - \bar{X}}{s_X}, \quad (1)$$

Where $\bar{X}$ and s_X are the mean and standard deviation across the whole sample. Patent applications and identifiers (country, year) remained in natural units.

Post-screening VIFs indicated no multicollinearity concerns (mean VIF 4.35–5.19; maximum VIF < 10) (Neter et al., 1996). Pairwise correlation coefficients were also examined, and variables with $|r| \geq 0.80$ were excluded in line with standard multicollinearity risk thresholds (Berry & Feldman, 1985). Internal consistency of the determinant blocks was confirmed using Cronbach's alpha, with $\alpha \geq 0.70$ considered acceptable.

3.2.1. Econometric Specification

The analysis proceeds in two stages. A baseline Fixed-Effects (FE) model first estimates within-country variation while controlling for unobserved heterogeneity (Wooldridge, 2016).

$$PA_{it} = \alpha_i + \lambda_t + \beta X_{it} + \varepsilon_{it}, \quad (2)$$

where PA_{it} denotes patent applications for country i at time t; X_{it} is the vector of standardized proxies; α_i and λ_t are country and year fixed effects; and ε_{it} is the idiosyncratic error term.

Tests revealed serial correlation (Wooldridge test) and heteroskedasticity (Modified Wald test), indicating that linear FE assumptions were violated (Wooldridge, 2016). Because patent data are count-based, non-negative, skewed, and include zeros, the Poisson Pseudo-Maximum Likelihood estimator with fixed effects (PPML-FE) was adopted as the main model. It yields consistent estimates under heteroskedasticity and handles zero outcomes (Silva & Tenreyro, 2006).

$$E[PA_{it} \mid \alpha_i, \lambda_t, X_{it}] = \exp(\alpha_i + \lambda_t + \beta X_{it}), \quad (3)$$

The final model is summarized as:

$$PA_{it} = f(X_{it}; \alpha_i, \lambda_t), \quad (4)$$

Estimation absorbs both country (α_i) and year (λ_t) effects with standard errors clustered at the country level. Although fixed effects reduce omitted-variable bias, time-varying endogeneity cannot be entirely ruled out; results are interpreted as within-country associations rather than causal effects. No instrumental-variable or system-GMM correction is applied. All estimations were conducted in Stata using the ppmlhdfe routine, with supporting procedures in R.

Model Diagnostics and Robustness Strategy

Diagnostic tests validated specification adequacy. The Hausman test confirmed the suitability of the fixed-effects estimator over the random effects (Papke & Wooldridge, 2023). The Wooldridge and Modified Wald tests detected serial correlation and heteroskedasticity, supporting the PPML-FE specification (Akbari & Naseri, 2022). Robustness procedures were multi-layered. They included parsimonious PPML-FE re-estimations using significant and low-correlated variables, residualization-based and drop-one sensitivity checks for correlated pairs, temporal-split validation (2010–2016 vs 2017–2023), and replication using natural-unit data. To further validate coefficient stability and inference reliability, two additional diagnostics were implemented: a Leave-One-Country-Out (LOCO) sensitivity test to assess the influence of individual country effects, and a Wild-Cluster Bootstrap-t (WCB) procedure with 1,000 replications clustered by country. LOCO confirmed the persistence of key coefficients across panels, while WCB results were largely conservative, suggesting robustness of direction but limited bootstrap significance under small-cluster adjustments. All models employed country-level cluster-robust standard errors. Convergence, log-pseudolikelihood, and Wald χ^2 statistics indicated numerical stability. Although potential time-varying endogeneity cannot be entirely excluded, the specification yields consistent within-country estimates aligned with PPML-FE assumptions (Baltagi et al., 2022).

4. RESULTS

4.1. Introduction

This chapter presents the empirical results examining how macro-level determinants influence patent activity across 65 countries from 2010 to 2023. Patent applications serve as the dependent variable, while 44 proxies grouped under nine determinants capture economic, institutional, and innovation dimensions. The analysis proceeds in three stages: (i) a descriptive overview of cross-income disparities and dataset adequacy, (ii) baseline Fixed-Effects (FE) estimation for initial inference and diagnostics, and (iii) Poisson Pseudo–Maximum Likelihood Fixed Effects (PPML-FE) models evaluating determinant effects across four panels—pooled, high-, upper-middle-, and lower-middle/low-income. Because explanatory proxies were standardized using z-scores, coefficients indicate relative influence; interpretation therefore emphasizes the direction and significance of relationships under cluster-robust, two-way fixed-effects estimation.

4.2. Descriptive Overview and Data Diagnostics

The diagnostic sequence began with descriptive verification of dataset adequacy, followed by multicollinearity and reliability tests. Table 3 summarizes patent applications across income groups, revealing wide disparities: high-income economies display the highest volumes, upper-middle-income economies show a pronounced skew driven by China, and lower-income economies record modest counts consistent with limited innovation capacity and institutional development.

Post screening Variance Inflation Factors (VIFs) were acceptable across panels (mean VIF 4.35–5.19; all max VIF < 10; Table 4). These results confirmed that retained variables were suitable for panel estimation. Appendix Table A3 lists the proxies that passed the VIF screen before correlation checks.

Pairwise correlation matrices were then used to detect residual dependencies. Coefficients with $|r| \geq 0.80$ were removed, while $0.70 \leq |r| < 0.80$ were monitored as "watchlist" pairs (Table 5). This process resulted in the exclusion of Access to Finance from the High-Income panel and of ICT Access, Infrastructure Index, Knowledge Creation, Fixed Broadband, and Creative Outputs from the pooled model, even though these proxies had previously passed the VIF screen.

Internal reliability within determinant groups was assessed using Cronbach's alpha, which ranged from 0.71 (Innovation and R&D) to 0.98 (Legal and Institutional Framework), exceeding the 0.70 benchmark and confirming the indicators' coherence (Appendix Table A4).

Together, these diagnostics ensured that the dataset was balanced, internally consistent, and free from severe multicollinearity, providing a sound basis for the subsequent Fixed-Effects and PPML-FE estimations.

Table 3: Descriptive Summary of Patent Applications by Income Group (2010–2023).

Variable	High	Upper-Middle	Lower-Middle	Low/Lower- Middle
Patent Applications	μ = 44 096.24, σ = 117 780.01, γ = 3.52, Range 3–621 453	μ = 60 735.67, σ = 266 308.87, γ = 4.90, Range 3–1 677 701	μ = 7 103.93, σ = 16 990.23, γ = 2.87, Range 1–90 298	μ = 26.7, σ = 20.17, γ = 0.82, Range 1–82

Note. μ = mean; σ = standard deviation; γ = skewness.

Table 4: Variance Inflation Factor (VIF) Results By Income Panel (Pre-Correlation Screen). Final Exclusions Based On Severe Correlation Are Shown In Table 5.

Panel	Mean VIF (Before)	Max VIF (Before)	Mean VIF (After)	Max VIF (After)	Proxies Dropped
High	70.15	1 354.52 (EXP)	4.35	9.20 (DCR)	6
Upper-Middle	15.16	141.66 (TRD)	5.03	10.02 (RDX)	8
Low/Lower-Middle	22.01	131.34 (EXP)	5.19	9.68 (GEV)	14
Pooled (All)	17.60	161.56 (EXP)	4.36	10.08 (GEV)	11

Note: Appendix Table A3 lists the dropped and kept proxies.

Table 5: Severe and Watchlist Correlation Pairs across Panels

Panel	Pair/r	Class	Action
High	ATF–DCR (0.878)	Severe	ATF excluded
	IER–COI (0.764); KNC–RDX (0.733); SBS–TRT (–0.768)	Watchlist	Retained
Upper-middle	PCI–RDX (0.714); IER–COI (0.754); SBS–TRT (–0.719)	Watchlist	Retained
Low/Lower-Middle	GPC–ATF (0.716); GPC–ICT (0.750); MOB–ICT (0.702); GEV–COC (0.721)	Watchlist	Retained
Pooled (All)	ICT–INT (0.889); INF–GEV (0.857); KNC–RDX (0.863); GEV–FSB(0.803); GEV–COI(0.801)	Severe	ICT, INF, KNC, FSB, COI excluded
	GEV–KWS (0.794); GEV–GPC (0.791); GEV–PSV (0.789); KWS–RDX(0.770); PSV–GPC (0.754); SBS–TRT(–0.747); SBS–CST(–0.700)	Watchlist	Retained

Note: Exclusions listed here override Appendix A3 VIF retention and apply to all subsequent estimations. Full correlation matrices for all income panels are available upon request for reproducibility

4.3. Baseline Fixed-Effects Estimation and Diagnostic Results

The Hausman specification test (Table 6) determined the appropriate estimation framework for each income-based panel. Across all four panels, the null hypothesis of no systematic difference between Fixed-Effects (FE) and Random-Effects (RE) estimators was rejected at the 1 percent level ($p < 0.01$), confirming that unobserved country-specific effects correlate with regressors and validating the FE estimator as consistent and efficient.

Table 6: Hausman Test Summary (Income level).

Panel	Chi-square (χ^2)	p-value	Preferred Model
High	54.27	0.000	Fixed Effects
Upper-middle	37.94	0.000	Fixed Effects
Low/Lower-middle	29.66	0.000	Fixed Effects
Pooled (All)	61.82	0.000	Fixed Effects

Note: The uniformly significant χ^2 values confirm that FE estimation reliably captures within-country variance over time.

Subsequent residual diagnostics evaluated model adequacy. The Wooldridge test (Appendix Table A5) detected first-order serial correlation ($p < 0.01$) in all panels, and the Modified Wald test indicated groupwise heteroskedasticity ($p < 0.01$). These results confirm the presence of non-spherical error structures, suggesting that standard linear FE models may yield inefficient inference for patent count data.

Baseline FE estimations established initial directional relationships before adopting the PPML-FE framework. Country and year fixed effects were included, with heteroskedasticity-robust standard errors clustered by country (Appendix Table A6). The correlation screen (Section 4.2) had already excluded Access to Finance in the High-Income panel and ICT Access, Fixed Broadband Subscriptions, Infrastructure Index, Knowledge Creation, and Creative Outputs in the pooled model, while retaining watchlist variables with $|r| < 0.80$.

Although the linear FE models reveal preliminary within-country relationships, their residual patterns justify a transition to Poisson Pseudo–Maximum Likelihood Fixed Effects estimation, which accommodates heteroskedasticity, corrects distributional irregularities, and ensures scale-consistent inference for patent count data.

4.4. Poisson Pseudo–Maximum Likelihood Fixed-Effects (PPML-FE)

Following the diagnostic evidence of heteroskedasticity and serial correlation, the study employed the Poisson Pseudo–Maximum Likelihood Fixed Effects (PPML-FE) estimator as the principal analytical model. PPML-FE is appropriate for count-based, non-negative patent data and remains consistent under general heteroskedasticity while naturally accommodating zero observations. Two-way fixed effects (country and year) were included to capture unobserved time-invariant heterogeneity and global shocks. All estimations used country-level cluster-robust standard errors, and no offset term was applied.

Table 7 summarizes the significant coefficients across four income panels, while Figures 2a–2d visualize the magnitudes and directions of the effects. Coefficients were estimated using standardized variables (z-scores), so magnitudes indicate relative rather than absolute strength.

4.4.1. High-Income Economies

Across eight determinants, 19 proxies were statistically significant in the high-income panel. Under Economic Performance and Market Size (ECON), GDP per Capita (GPC, $p = 0.002$) showed a strong positive association with patent activity, whereas Industry Activity (IND, $p < 0.001$) showed a negative association. Within Investment and Financial Environment (INVF), Tax Revenue (TAX, $p < 0.001$) and Domestic Credit to the Private Sector (DCR, $p = 0.013$) were strongly positive. In contrast, Foreign Direct Investment (FDI, $p < 0.001$) had an adverse effect. For Innovation and R&D (INRD), Knowledge Creation (KNC, $p = 0.007$) and High-Tech Exports (HTE, $p = 0.038$) were both positively associated with patenting. In Education and Human Capital (EDUC), Knowledge Workers (KWS, $p = 0.001$) contributed positively, while the Human Capital and Research Index (HCI, $p = 0.012$) contributed negatively. INFR factors uniformly constrained patent performance: Mobile Subscriptions (MOB, $p < 0.001$), Access to Electricity (ELE, $p = 0.003$), Infrastructure Index (INF, $p = 0.012$), and Productive Capacity Index (PCI, $p = 0.014$) were all negatively associated with patent performance. Within Regulatory and Business Environment (REGB), Starting a Business (SBS, $p < 0.001$), Cost of Business Start-Up (CST, $p < 0.001$), and Paying Tax (SPT, $p = 0.043$) were positive, whereas Protecting Minority Investors (PMI, $p = 0.043$) was negative. Finally, under Legal and Institutional Framework (LEGL), Government Effectiveness (GEV, $p < 0.001$) was positive, and within Intellectual Property and Innovation Outputs (IPIO), Innovation Efficiency Ratio (IER, $p < 0.001$) remained negative. Figure 2a visualizes the significant proxies and their magnitude.

Figure 2a. Significant Proxies- High-Income

4.4.2. Upper-Middle-Income Economies

Across nine determinants, 17 proxies were statistically significant in the upper-middle-income panel. Under Economic Performance and Market Size (ECON), GDP Growth (GGW, $p < 0.001$) showed a strong positive association with patent activity, while Trade (TRD, $p = 0.047$) had an adverse effect. Within Investment and Financial Environment (INVF), both Tax Revenue (TAX, $p = 0.002$) and Access to Finance (ATF, $p < 0.001$) were positively associated with patenting, underscoring the joint role of fiscal stability and financial access. For Innovation and R&D (INRD), R&D Expenditure (RDX) exerted a robust positive influence ($p < 0.001$). In Education and Human Capital (EDUC), Knowledge Workers (KWS, $p < 0.001$) and Tertiary Enrollment (TER, $p = 0.003$) contributed positively, highlighting human-capital intensity as a key enabler of innovation. In Infrastructure and Digital Connectivity (INFR), Infrastructure effects were mixed: the Infrastructure Index (INF, $p = 0.050$) and Mobile Subscriptions (MOB, $p = 0.053$) were mildly positive, whereas Fixed Broadband (FSB, $p = 0.015$) and ICT Access (ICT, $p = 0.026$) were negative. Under Regulatory and Business Environment (REGB), Starting a Business (SBS, $p<0.001$) and Cost of Start-Up (CST, $p = 0.040$) both showed adverse effects. In the Legal and Institutional Framework (LEGL) category, Political Stability (PSV, $p = 0.003$) was negatively associated with patenting, and in the Intellectual Property and Innovation Outputs (IPIO) category, Creative Outputs (COI, $p < 0.001$) were also negatively associated with patenting. Lastly, under Property and Infrastructure Development (PROP), Registering Property – Time (RPT, $p < 0.001$) positively influenced patent performance, whereas Registering Property – Procedures (RPP, $p = 0.052$) remained negative. Figure 2b visualizes the significant proxies and their magnitude.

Figure 2b: Significant Proxies- Upper-Middle-Income.

4.4.3. Lower-Middle & Low-Income Economies

Across eight determinants, 12 proxies were statistically significant in the lower-middle- and low-income panel. Under Economic Performance and Market Size (ECON), GDP Growth (GGW, $p = 0.012$) was positively associated with patent activity, while Gross Capital Formation (GCF, $p = 0.033$) exerted a negative influence. Within Investment and Financial Environment (INVF), Access to Finance (ATF, $p = 0.001$) showed a strong positive effect, whereas Tax Revenue (TAX, $p < 0.001$) showed an adverse impact. For Innovation and R&D (INRD), Knowledge Creation (KNC, $p = 0.01$) displayed a significant negative association with patenting. In Education and Human Capital (EDUC), Tertiary Enrolment (TER, $p < 0.001$) contributed positively, but STEM Graduates (STG, $p = 0.009$) contributed negatively. Infrastructure constraints persisted, as the Infrastructure and Digital Connectivity (INFR) variable Infrastructure Index (INF, $p = 0.007$) showed a negative coefficient. Under Regulatory and Business Environment (REGB), Protecting Minority Investors (PMI, $p = 0.005$) showed a strong positive association, whereas Paying Tax (SPT, $p < 0.001$) showed a negative association. Within Legal and Institutional Framework (LEGL), Control of Corruption (COC, $p < 0.001$) maintained a strong positive effect, and under Intellectual Property and Innovation Outputs (IPIO), Creative Outputs (COI, $p < 0.001$) also showed a strong positive effect. Figure 2c visualizes the significant proxies and their magnitude.

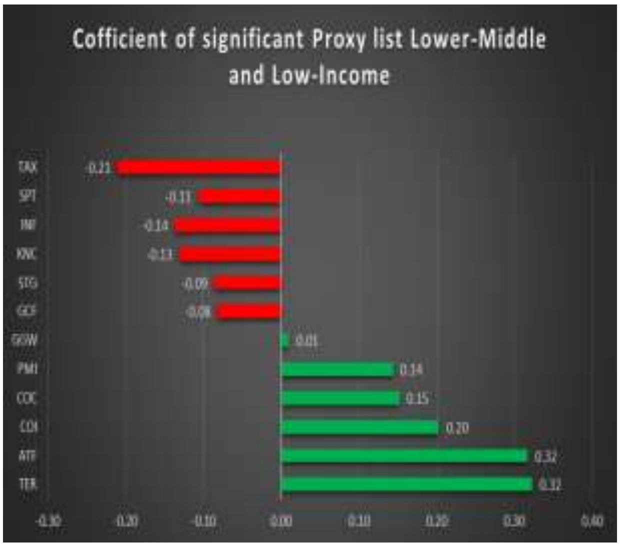

Figure 2c: Significant Proxies- Low/Lower-Middle-Income.

4.4.4. Pooled (All) Economies

Across eight determinants, 16 proxies were statistically significant in the pooled all-income panel. Under Economic Performance and Market Size (ECON), GDP per Capita (GPC, p = 0.031) was positive, while Industry Activity (IND, p < 0.001) remained strongly negative. Within Investment and Financial Environment (INVF), Access to Finance (ATF, p < 0.001) showed a consistent positive influence, whereas Foreign Direct Investment (FDI, p < 0.001) and Getting Credit (SGC, p = 0.002) exhibited significant negative associations. Tax Revenue (TAX, p = 0.025) was negative, indicating that financial depth supports patenting more effectively than capital inflows or Tax expansion. For Innovation and R&D (INRD), both R&D Expenditure (RDX, p = 0.038) and High-Tech Exports (HTE, p = 0.061) were positive, reflecting the role of research and technology diffusion in global patenting. In Education and Human Capital (EDUC), Tertiary Enrolment (TER, p < 0.001) and Knowledge Workers (KWS, p < 0.001) positively influenced patent output, underscoring human-capital effects across economies. Infrastructure variables Infrastructure and Digital Connectivity (INFR) were uniformly positive: Internet Use (INT, p = 0.001) and Access to Electricity (ELE, p = 0.003) contributed strongly to inventive performance. Under Regulatory and Business Environment (REGB), Time Required to Start a Business (TRT, p = 0.007) was positive, while Business Environment (BEV, p = 0.016) was negative. Within Legal and Institutional Framework (LEGL), Government Effectiveness (GEV, p = 0.003) remained a key positive institutional factor. Under Property and Infrastructure Development (PROP), Registering Property – Time (RPT, p = 0.089) also showed a positive though modest association with patent activity. Figure 2d visualizes the significant proxies and their magnitude.

Figure 2d: Significant Proxies Pooled (All)- Income.

Table 7: PPML-FE Results By Income Group (Significance At 1%, 5%, And 10% Levels) Proxies With the Coefficient.

Determinant	High	Upper-Middle	Low/ Lower-Middle	Pooled (All)
ECON	GPC***(0.178, 0.058), IND***(-0.189, 0.039)	GGW*** (0.045, 0.012), TRD**(-0.183, 0.092)	GGW**(0.009, 0.004), GCF**(-0.081, 0.038)	GPC**(0.177, 0.082), IND***(-0.262, 0.053)
INVF	TAX***(0.180, 0.022), FDI***(-0.111, 0.010) DCR**(0.094, 0.038)	TAX***(0.148, 0.040), ATF***(0.264,0.084)	ATF***(0.317, 0.095), TAX***(-0.210, 0.042)	ATF***(0.325, 0.056), FDI***(-0.101, 0.014), SGC**(-0.084, 0.028), TAX**(-0.173, 0.078)
INRD	KNC***(0.046, 0.017), HTE**(0.071, 0.035)	RDX***(0.249, 0.034)	KNC***(-0.13, 0.051)	RDX**(0.148, 0.071), HTE*(0.126, 0.067)

EDUC	KWS***(0.040, 0.012), HCI**(-0.048, 0.019)	KWS***(0.140, 0.019), TER***(0.123, 0.042)	TER***(0.322, 0.085), STG***(-0.085, 0.033)	TER***(0.253, 0.046), KWS*** (0.072, 0.015)
INFR	MOB***(-0.100, 0.025), ELE***(-0.006,0.002), INF**(-0.064, 0.026), PCI**(-0.087, 0.036)	INF**(0.070, 0.036), MOB*(0.086, 0.045), FSB**(-0.126, 0.052), ICT**(-0.111,0.050)	INF***(-0.136, 0.050)	INT***(0.170, 0.052), ELE***(0.325, 0.110)
REGB	SBS***(0.136,0.035), CST***(0.133, 0.028), SPT**(0.038, 0.019), PMI**(-0.061, 0.030)	SBS***(-0.082, 0.022), CST**(-0.05, 0.025)	PMI***(0.144, 0.051), SPT***(-0.106, 0.019)	TRT***(0.046, 0.017), BEV**(-0.042,0.017)
LEGL	GEV*** (0.118, 0.031)	PSV***(-0.091, 0.031)	COC***(0.152, 0.028)	GEV***(0.152,0.052)
IPIO	IER*** (-0.070, 0.014)	COI***(-0.073, 0.021)	COI***(0.202, 0.043)	–
PROP	–	RPT**(0.589, 0.017), RPP*(-0.110, 0.057)	–	RPT*(0.038, 0.023)

Note. Values in parentheses are (coefficient, standard error). All models were estimated using Poisson Pseudo-Maximum-Likelihood with two-way fixed effects (country and year) and cluster-robust standard errors. No offset term was applied. Pseudo R^2 values across panels ranged from 0.9989 to 0.9998. All models converged successfully and were jointly significant at $p < 0.01$. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

While the PPML-FE estimations yield stable and interpretable coefficients across income groups, further diagnostic testing is required to confirm that the observed relationships are not driven by residual collinearity among closely related proxies. The following subsection, therefore, applies residualization and model-parsimony checks to ensure that retained indicators contribute unique and independent explanatory power.

4.5. Residualization and Model Parsimony Tests

The residualization and drop-one robustness tests assessed whether moderate correlations among watchlist pairs ($|r| \approx 0.70$–0.79) influenced the estimates. As summarized in Table 8, most pairs provided independent information and were retained in parsimonious PPML-FE models, along with the significant proxies reported in Section 4.4.

Table 8: Watchlist Correlation Pairs and Final Retention Decisions in Residualization Tests.

Panel	Key pairs tested	Outcome (kept/dropped)
High	COI–IER, RDX–KNC, TRT–SBS	IER, KNC, SBS retained
Upper-Middle	PCI–RDX, IER–COI, SBS–TRT	RDX, COI, SBS retained
Low/Lower-Middle	GPC–ATF, GEV–COC, ICT -GPC, ICT-MOB	ATF, COC retained
Pooled (All)	GEV-KWS, GEV-GPC, GEV-PSV, KWS-RDX, GPC, PSV, SBS-TRT, SBS-CST	GEV, KWS, GPC, RDX, TRT retained

Having verified the internal consistency of the retained proxies, the analysis next evaluates the robustness of the PPML-FE findings across alternative estimation forms, data scales, and time periods. These checks collectively validate the reliability and structural stability of the core results.

4.6. Robustness and Validation

A series of robustness procedures verified the stability of the Poisson Pseudo–Maximum Likelihood Fixed Effects (PPML-FE) estimations across model forms, data scales, and time periods.

4.6.1. Comparison with the Linear FE Baseline

The PPML-FE results remained consistent with the earlier linear fixed-effects estimates (Appendix Table A6), confirming that the nonlinear specification captures the same within-country patterns while accommodating heteroskedasticity in patent counts. High-income economies sustained positive effects for Gross Domestic Product per Capita and knowledge-based indicators, while industrial and infrastructure proxies remained negative. Upper-middle- and lower-income groups similarly preserved the positive influence of education and institutional quality.

4.6.2. Validation across Scales and Parsimony

Re-estimation using unstandardized (natural-unit) data (Appendix Table A9) produced identical coefficient signs and significance tiers, demonstrating that inference is invariant to normalization. Simplified PPML-FE models (Appendix Table A7) and residualization tests confirmed that moderate intercorrelations ($|r| \approx 0.70$–0.79) neither biased coefficient magnitudes nor altered determinant directions.

4.6.3. Temporal and Diagnostic Robustness

A split-sample analysis for 2010–2016 and 2017–2023 (Appendix Table A8) verified the persistence of key determinants—Access to Finance, Tertiary Enrolment, and Government Effectiveness—while minor variations in infrastructure proxies reflected gradual technological shifts. Post-estimation diagnostics (Appendix Table A10) further reinforced stability: the Leave-One-Country-Out (LOCO) test confirmed that no single country unduly influenced the results, and the Wild-Cluster Bootstrap-t (WCB) procedure, though yielding conservative p-values, supported directionally consistent inference under alternative clustering assumptions.

Overall, these robustness checks affirm that the observed relationships among finance, education, and governance are structural rather than model-specific, underscoring the reliability of the PPML-FE framework across income groups and time periods.

4.7. Discussion

4.7.1. Framing the Discussion

Building on Section 4, this discussion interprets how key proxy indicators shape patent activity across income groups. Tertiary Enrolment, Knowledge Workers, Access to Finance, Government Effectiveness, and Infrastructure emerge as important but income-contingent drivers of patenting, confirming that human capital, financial accessibility, governance quality, and infrastructure conditions remain central to innovation (Ferreira et al., 2024; Ma & Chang, 2023; Schofer et al., 2021). In contrast, Industry Activity often weakens patenting, while Foreign Direct Investment exhibits adverse or mixed effects depending on institutional strength (Benassi et al., 2022; Rao et al., 2024; Xu & Li, 2021). Tax Revenue displays development-contingent effects: it is positive in high- and upper-middle-income economies but negative in lower-income and pooled estimations, where fiscal rigidity can constrain inventive activity. (Bechlioulis et al., 2023).

4.7.2. Cross-Panel Synthesis and Comparative Interpretation

Innovation outcomes depend on the interaction among economic performance (ECON), finance (INVF), human capital (EDUC), and institutional quality (LEGL/REGB), while infrastructure and regulation have context-specific roles.

In high-income economies, GDP per Capita, Tax Revenue, Knowledge Creation and Knowledge Workers, Ease of Doing Business, Cost of Starting Business, and Government Effectiveness positively influence patenting, reflecting how economic scale, fiscal capacity, skilled labour, and governance and regulatory quality enable coordinated resource allocation (Bechlioulis et al., 2023; Ferreira et al., 2024; Schofer et al., 2021). Similarly, Domestic Credit to the Private Sector, High-Technology Exports, and Ease of Paying Taxes further facilitate patenting by easing financial constraints and reducing procedural frictions faced by innovators. In contrast, Industry Activity and Foreign Direct Investment, together with infrastructure-related proxies such as Mobile Subscriptions, Access to Electricity, and the Innovation Efficiency Ratio, exhibit diminishing or saturation effects as technological systems mature and marginal expansion outpaces productive innovation. Human Capital and Research Index, Protecting Minority Investors, Infrastructure Index, and Productive Capacity Index display negative associations with patenting in high-income contexts, suggesting that institutional rigidity and efficiency constraints can limit incremental inventive activity. Overall, these patterns are consistent with Schumpeterian arguments that advanced economies experience slower marginal innovation once industries, infrastructure networks, and market structures reach high levels of maturity(Aghion & Howitt, 1992; Benassi et al., 2022).

In upper-middle-income economies, patent activity is shaped by complex innovation inefficiencies rooted in institutional quality, financial structure, and political context. Cross-country evidence indicates that technological upgrading and patent enforcement generate uneven innovation gains, particularly in environments characterised by policy uncertainty and limited absorptive capacity (Qamruzzaman et al., 2021; Sharma et al., 2022; Yoruk et al., 2023). Political instability further constrains inventive activity by undermining investment confidence and coordination (Krammer & Kafouros, 2022; Tabash et al., 2023; J.-Z. Wang et al., 2024). Within this group, GDP Growth, Tax Revenue, Access to Finance, R&D Expenditure, Knowledge Workers, and Tertiary Enrolment exhibit a strong influence on Patenting. In contrast, the Infrastructure Index and the Ease of Registering Property exert positive influences on patenting, indicating that fiscal capacity, human capital accumulation, financial access, and selected infrastructure improvements can support inventive activity even when institutional systems remain partially consolidated. In contrast, Ease of Doing Business and Creative Outputs have a strong negative association with patenting. Similarly, Cost of Business Start, Trade openness, Broadband Subscriptions, ICT Access, and Political Stability exhibit negative associations with patenting, reflecting adjustment frictions, regulatory burdens, and coordination challenges during transitional development stages. Taken together, these patterns suggest that innovation performance in upper-middle-income economies depends less on individual inputs in isolation than on the interaction among institutional, political, and financial systems, as countries navigate the shift from factor-driven growth toward more innovation-based development paths (Benassi et al., 2022; Bruno et al., 2023; Kim & Yoo, 2024).

In lower-middle- and low-income economies, Access to Finance, Tertiary Enrolment, Protecting Minority Investors, Control of Corruption, and Creative Output were found to be significant patenting enablers. Likewise, GDP Growth also positively influences patenting, indicating that institutional trust, financial inclusion, and the effective mobilisation of human capital are central to building inventive capacity in resource-constrained settings (Aldieri et al., 2023; Jalil et al., 2023; Meyer et al., 2024). In contrast, Tax Revenue and the Ease of Paying Taxes, together with Knowledge Creation, Infrastructure-related indicators (the Infrastructure Index), and STEM Graduates, exhibit adverse associations with patent activity. These negative effects reflect fiscal rigidity, weak absorptive capacity, and structural mismatches between education systems, infrastructure provision, and industrial demand, which limit the translation of skills and public investment into sustained innovation outcomes (Balsalobre-Lorente et al., 2021; Khan et al., 2023; Loyalka et al., 2021; Okoye et al., 2022). Corporate tax burdens and underdeveloped research ecosystems further constrain inventive activity in these economies. Strengthening governance credibility, deepening access to finance, improving corruption control, and aligning education and infrastructure investments with productive sectors, therefore, remain essential for sustaining patent growth and narrowing systemic innovation gaps in lower-income contexts.

Across the pooled sample, Access to Finance, Tertiary Enrollment, Knowledge Workers, Government Effectiveness, Infrastructure (Internet and Electricity access), and Time to Start a Business emerged as significant patenting enablers, reflecting complementarities between human capital intensity, governance quality, administrative efficiency, and connectivity at the global level (Ferreira et al., 2024; Kim & Yoo, 2024; J. Li & Lou, 2024; Pal et al., 2025; Reverte, 2022). Similarly, GDP per Capita and R&D Expenditure also emerge as positive drivers of patenting, indicating that economic scale and innovation-oriented production structures continue to matter in aggregate cross-country estimations. In contrast, Industry Activity emerged as a significant hurdle to patenting; likewise, constraints in accessing credit, Tax Burdens, and Business Environments are associated with weaker inventive performance, while depressing patenting outcomes in the pooled model (Benassi et al., 2022; Fikru & Shen, 2025; Rao et al., 2024). These patterns reveal a developmental gradient in which global innovation outcomes reflect a combination of coordination and efficiency in advanced economies, institutional adaptation in transitional systems, and foundational investment dynamics in emerging contexts (Bambi & Pea-Assounga, 2025; Gyedu et al., 2021). Supporting evidence from recent cross-country studies further indicates that improvements in electricity access and digital infrastructure facilitate technology adoption and patenting, particularly in developing settings, whereas restrictive credit conditions and weak business environments constrain inventive activity where institutional capacity and financial inclusion remain limited (Cotter et al., 2021; Murshed, 2023; Wen et al., 2022; H.-C. Yang et al., 2022).

4.8. Determinant-Wise Discussion and Theoretical Linkages

4.8.1. Endogenous Growth Theory (EGT)

Endogenous Growth Theory (EGT) interprets innovation as the outcome of sustained investment in knowledge, skills, and productive capacity. The positive effects of GDP per Capita, GDP Growth, Access to Finance, Tertiary Enrolment, and Knowledge Workers illustrate how market expansion, financial depth, and education reinforce one another in generating new ideas and fostering cumulative innovation (Bambi & Pea-Assounga, 2025; Etro, 2023; W. Li et al., 2024; Mabrouki, 2023). Empirical evidence confirms that absorptive capacity increases when human capital formation and financial inclusion expand simultaneously, enabling economies to internalize external knowledge and transform it into inventive output (Jalil et al., 2023; Pal et al., 2025). Conversely, occasional negative or neutral effects on Tax Revenue suggest that inefficient or distortionary fiscal structures may divert resources away from private R&D and weaken long-term innovation incentives (Bechlioulis et al., 2023; Fikru & Shen, 2025). Overall, these results reaffirm EGT's central premise that innovation becomes self-reinforcing when education, finance, and economic growth interact productively, enabling sustained knowledge accumulation and technological progress (Grossman & Helpman, 1993; Lucas, 1988; Romer, 1990).

4.8.2. Schumpeterian Innovation Theory (SIT)

Schumpeterian Innovation Theory (SIT) conceives innovation as a cyclical process of creative destruction, in which entrepreneurial competition continually transforms technologies, products, and industrial organization. The positive influences of R&D Expenditure and High-Technology Exports, along with the mixed or context-dependent effects of Creative Outputs, are positive in lower-income economies yet negative in several upper-middle-income contexts, illustrating how technological renewal operates differently across development stages (Bandura, 2025; Tajaddini & Gholipour, 2020). By contrast, the negative coefficients for Industry Activity and Foreign Direct Investment, particularly visible in the high-income and pooled panels, suggest that industrial maturity and reliance on foreign capital can suppress domestic experimentation and slow structural renewal (Ahmad, 2021; Feitosa & Garcia, 2024; Ruan & Chen, 2025; Valacchi et al., 2021). Overall, SIT clarifies why R&D-driven renewal and technological competition sustain patent creation, whereas saturated or externally dominated production systems erode inventive dynamism (Aghion & Howitt, 1992; Audretsch et al., 2023; Schumpeter, 1934, 1942).

4.8.3. Institutional and Systems Theory (IST)

Institutional and Systems Theory (IST) conceptualizes innovation as a systemic process embedded in governance quality, legal reliability, and infrastructural coordination. The strong positive effects of Government Effectiveness, and particularly within lower-income groups, Control of Corruption, and Protecting Minority Investors, illustrate how credible institutions enhance trust, reduce transaction costs, and encourage inventive risk-taking (Halynskyi & Telizhenko, 2024; Ibrahimi et al., 2025; Mitu et al., 2024; Reverte, 2022). Infrastructure and regulatory determinants play conditional roles: expanding Internet Use and Access to Electricity facilitate participation in knowledge networks and technology diffusion (Adedoyin et al., 2022; Cotter et al., 2021), whereas indicators such as Mobile Subscriptions or a composite Infrastructure Index show diminishing returns when physical expansion outpaces institutional adaptation (Kim & Yoo, 2024; Lumeng et al., 2023). Administrative variables, including Time Required to Start a Business and Registering Property Time, further demonstrate that procedural efficiency and transparent registration processes strengthen the legal infrastructure required for sustained innovation (Lehtimäki, 2025; Morano et al., 2023). These results echo Freeman's (1987) and Lundvall's (1992), affirming that innovation flourishes when governance, law, and infrastructure evolve cohesively.

4.8.4. Robustness and Temporal Stability

Robustness analyses confirm the internal consistency of the Poisson Pseudo–Maximum Likelihood Fixed Effects framework across models and time periods (Pfaffermayr, 2020). Results remain stable under the parsimonious, natural-unit, and temporal-split estimations for 2010–2016 and 2017–2023. The consistent direction and significance of the coefficients indicate that the observed relationships are structural rather than model-specific. Post-estimation diagnostics—the Leave-One-Country-Out and Wild-Cluster Bootstrap-t tests—further validate coefficient stability and inference reliability across income groups, confirming that no single country drives the results and that alternative clustering assumptions yield directionally consistent though more conservative inference.

Excluding non-significant proxies leaves Access to Finance, Tertiary Enrolment, Knowledge Workers, and Government Effectiveness as strongly and positively significant. At the same time, Industry Activity, Foreign Direct Investment, and Tax Revenue remain negative, confirming interpretive stability. Re-estimation in natural units produced identical coefficient signs and significance levels, demonstrating that z-score standardization did not distort relationships.

The temporal split underscores shifting emphases in the determinants of innovation. During 2010–2016, Access to Finance and Tertiary Enrolment were the most influential, reflecting foundational expansion of financial systems and human capital accumulation that laid the groundwork for inventive activity. In contrast, the 2017–2023 period was characterized by the growing importance of Government Effectiveness and Control of Corruption, underscoring the centrality of institutional strengthening in sustaining inventive capacity as economies matured. These longitudinal patterns confirm that the observed relationships represent enduring structural dynamics rather than model-specific artifacts. The persistent negative influence of Industry Activity and Tax Revenue further illustrates the constraining effects of industrial and fiscal rigidity on innovation over time. Overall, patent activity remains systematically shaped by the interdependence of finance, human capital, and governance, reaffirming the sustained relevance of Endogenous Growth Theory and Institutional and Systems Theory in explaining long-term innovation dynamics.

4.8.5. Scope Conditions and Limitations

The cross-country panel design enables broad comparison but limits micro-level causal precision. While two-way fixed effects reduce country- and year-specific heterogeneity, potential endogeneity between patenting and its determinants may persist; results should therefore be interpreted as associative rather than causal (Correia et al., 2020; Yoruk et al., 2023). Standardization through z-scores enhanced comparability but may have compressed natural variance. Re-estimation in natural units confirmed that this transformation did not alter coefficient direction or significance. Interpolation and limited imputation, applied to maintain a balanced panel, may have reduced short-term volatility. Proxy selection was guided by theoretical relevance and data availability, with indicators such as Government Effectiveness and Knowledge Workers capturing observable dimensions of broader institutional and human-capital constructs.

The nine determinant domains capture central economic and institutional mechanisms but exclude cultural and sector-specific dynamics. Integrating Endogenous Growth, Schumpeterian Innovation, and Institutional and Systems Theories provides conceptual breadth yet omits behavioural and evolutionary perspectives. The Poisson Pseudo-Maximum Likelihood Fixed Effects estimator, although robust to heteroskedasticity and zero counts, remains sensitive to unmodeled feedback between patenting and its drivers (Correia et al., 2020; Silva & Tenreyro, 2006). Nonetheless, post-estimation diagnostics—the Leave-One-Country-Out and Wild-Cluster Bootstrap-t tests—help mitigate country-specific bias and reinforce inference reliability (Cameron et al., 2008; MacKinnon et al., 2023).

Moreover, heterogeneous effects across income groups, for instance, the positive association of Tax revenue in middle-income economies versus its negative influence in lower-income contexts, underscore that structural conditions moderate these relationships (Castellacci et al., 2022). Despite these constraints, the consistent direction and significance of the coefficients across robustness checks lend credibility to the findings. The study thus provides a reliable macro-level foundation for understanding how economic, financial, educational, and institutional factors shape inventive performance over time.

4.9. Policy and Practical Implications

Policy effectiveness depends on institutional maturity and coordination capacity. The positive influence of Access to Finance, Tertiary Enrolment, Knowledge Workers, and Government Effectiveness indicates that innovation expands when education, finance, and governance operate synergistically, consistent with the premises of Endogenous Growth Theory and Institutional and Systems Theory (Bambi & Pea-Assounga, 2025; Jalil et al., 2023).

In high-income economies, the adverse effects of Industry Activity and Foreign Direct Investment point to a shift from quantitative expansion toward qualitative renewal through research translation, IP commercialization, and technological diversification, aligning with Schumpeter's view that mature systems require continuous creative renewal (Ruan & Chen, 2025; Valacchi et al., 2021). Similarly, the adverse effects of infrastructure-related proxies and the innovation efficiency ratio indicate that in an advanced economy, these proxies are already saturated. A positive association between tax and credit to the private sector business environment suggests that an advanced economy needs to focus more on these.

In upper-middle-income economies, where growth momentum coexists with coordination gaps, improving regulatory efficiency is pivotal. Positive effects for finance, education, and Tax Revenue contrast with negative coefficients for digital connectivity and administrative indicators such as Fixed Broadband Subscriptions and starting a Business/Cost of Start-Up, underscoring the need to integrate digital infrastructure with research ecosystems and to simplify procedures that delay patenting (Kim & Yoo, 2024; Morano et al., 2023).

In lower-middle- and low-income economies, the significance of Control of Corruption, Protecting Minority Investors, and Creative Outputs underscores the importance of governance integrity and legal protection as preconditions for innovation. Policies should strengthen intellectual property enforcement, expand research funding, and align tertiary education with industrial demand (Halynskyi et al., 2024; Mitu et al., 2024). Building institutional trust and transparency can convert latent human capital into active inventive capacity.

At the global level, the combined significance of finance, education, and governance calls for coordinated innovation policies that link universities, financial institutions, and regulators. Streamlining Time Required to Start a Business and Register Property – Time correlates with stronger patenting, reinforcing the value of predictable, transparent administrative processes. Transparent governance, data-driven evaluation, and equitable access to R&D resources can enhance both the quality and volume of patenting across diverse institutional contexts (Ibrahimi et al., 2025).

4.10. Directions for Future Research

Future studies can extend the current framework in several directions. Applying instrumental-variable or dynamic panel approaches would strengthen causal inference and capture the long-term impact of financial, educational, and institutional reforms on inventive output.

Expanding the analysis to sectoral datasets could reveal how Access to Finance, Tertiary Enrolment, and Government Effectiveness function within specific technological or industrial systems, linking firm-level R&D behaviour to national innovation performance.

Qualitative extensions could help elucidate mechanisms that lie beyond the reach of econometric analysis. In-depth case studies or interviews with policymakers, R&D managers, and innovation intermediaries could trace how governance reforms, financing arrangements, and education–industry linkages translate into inventive capacity, particularly in lower-income contexts. Such qualitative inquiry would also be valuable for explaining findings that diverge from conventional expectations, including negative associations between certain determinants and patenting observed in specific income groups, where institutional practices and contextual constraints may play a decisive role.

Finally, examining interactions between digital connectivity and institutional quality could show whether strong governance amplifies or moderates technology's benefits. Such analyses would deepen understanding of how finance, education, and governance collectively sustain innovation across stages of development.

5. CONCLUSION

Patent activity arises from the interaction of financial accessibility, human capital, and institutional integrity. This study develops an income-based comparative framework covering 65 economies from 2010 to 2023, enabling a systematic assessment of global and context-specific drivers of innovation.

Access to Finance, Tertiary Enrollment, and Knowledge Workers strengthen inventive output across multiple income panels, while institutional factors operate in a panel-specific effects. In contrast, Industry Activity is typically negative, Foreign Direct Investment remains negative in high-income and pooled economies, and Tax Revenue shows mixed effects, positive in high- and upper-middle-income economies but negative in lower-income and pooled contexts. Economies that coordinate finance, education, and governance achieve stronger patent performance; those constrained by fiscal rigidity or industrial saturation experience weaker outcomes. Across income-group estimations, the findings are consistent with structurally differentiated drivers of patent activity rather than model-specific artifacts. rather than their dependence on the model.

By integrating Endogenous Growth, Schumpeterian Innovation, and Institutional and Systems Theories, the analysis demonstrates that long-term inventive performance depends on the convergence of education, finance, and governance. Human-capital formation and financial inclusion generate the momentum for innovation, while institutional coherence preserves it over time.

Ultimately, innovation represents both an economic and a governance challenge. Nations that widen credit access, strengthen higher education, and maintain transparent, capable institutions convert resources into enduring inventive capacity. Innovation policy should therefore be approached not as a sectoral initiative but as a coordinated institutional strategy aligning finance, education, and governance to sustain broad-based innovative growth.

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APPENDIX

Table A1: Determinants, Proxies, and Units of Measurement

Determinant	Proxy	Full name	Unit of measurement	Primary data source
ECON (Economic Performance & Market Size)	GPC	GDP per Capita	Current US dollars (actual)	World Bank WDI
	GGW	GDP Growth	Annual %	World Bank WDI
	GCF	Gross Capital Formation	% of GDP	World Bank WDI
	TRD	Trade	% of GDP	World Bank WDI
	EXP	Exports of Goods and Services	% of GDP	World Bank WDI
	IND	Industry Activity	Industry, value added, % of GDP	World Bank WDI
INVF (Investment & Financial Environment)	FDI	FDI Inflows	% of GDP	World Bank WDI
	TAX	Tax Revenue	% of GDP	World Bank WDI
	DCR	Domestic Credit to Private Sector	% of GDP	World Bank WDI
	SGC	Getting Credit	Score, 0–100	World Bank Doing Business (archived), Getting Credit score.
	ATF	Access to Finance	Score, 0–100	WIPO Global Innovation Index (Finance/Market sophistication sub-pillar)
INRD (Innovation & R&D Activity)	RDX	R&D Expenditure	% of GDP	World Bank WDI
	HTE	High-Tech Exports	% of manufactured exports	World Bank WDI
	STA	Sci. & Technical Journal Articles	Count (number)	World Bank WDI
	KNC	Knowledge Creation	Score, 0–100	WIPO Global Innovation Index.
EDUC (Education & Human Capital)	GED	Government Expenditure on Education	% of GDP	World Bank WDI
	TER	Gross Enrollment Ratio, Tertiary	% of relevant age group	World Bank WDI
	HCI	Human Capital & Research Index	Score, 0–100	WIPO Global Innovation Index.
	STG	STEM Graduates	%b of tertiary graduates	GII indicator "Graduates in science & engineering." WIPO
	KWS	Knowledge Workers	Score, 0–100	WIPO Global Innovation Index.
INFR (Infrastructure & Digital Connectivity)	ELE	Access to Electricity	% of population	World Bank WDI
	INT	Individuals Using the Internet	% of population	World Bank WDI (source: ITU)
	FSB	Fixed Broadband Subscriptions	Per 100 people	World Bank WDI (source: ITU)
	MOB	Mobile Cellular Subscriptions	Per 100 people	World Bank WDI (source: ITU)
	INF	Infrastructure Index	Score, 0–100	WIPO Global Innovation Index.
	ICT	ICT Access	Score, 0–100	WIPO Global Innovation Index (ICT access measure)
	PCI	Productive Capacities Index	Index, 0–100	UNCTAD PCI.
REGB (Regulatory & Business Environment)	EBD	Ease of Doing Business	Score, 0–100	World Bank WDI/Doing Business
	SPT	Paying Tax	Score, 0–100	World Bank Doing Business, Paying Tax.
	SBS	Starting a Business	Score, 0–100	World Bank Doing Business, Starting a Business.
	PMI	Protecting Minority Investors	Score, 0–100	World Bank Doing Business, PM Investor protection.
	BEV	Business Environment Index	Score, 0–100	WIPO Global Innovation Index.
	TRT	Time Required to Start a Business	Days	World Bank Doing Business
	CST	Cost of Business Start-Up	% of GNI per capita	World Bank Doing Business/WDI

		Procedures		
LEGL (Legal & Institutional Framework)	GEV	Government Effectiveness	WGI estimate, −2.5 to +2.5	World Bank WGI
	COC	Control of Corruption	WGI estimate, −2.5 to +2.5	World Bank WGI.
	PSV	Political Stability & Absence of Violence/Terrorism	WGI estimate, −2.5 to +2.5	World Bank WGI.
	ROL	Rule of Law	WGI estimate, −2.5 to +2.5	World Bank WGI.
	RUQ	Regulatory Quality	WGI estimate, −2.5 to +2.5	World Bank WGI.
IPIO (Innovation Performance & Outputs)	COI	Creative Outputs Index	Score, 0–100	WIPO Global Innovation Index (Output pillar).
	GII	Global Innovation Index (overall)	Score, 0–100	WIPO GII (overall score).
	IER	Innovation Efficiency Ratio	Index (ratio of outputs to inputs)	WIPO GII methodology.
PROP (Property & Infrastructure Development)	RPT	Registering Property – Time	Days	World Bank Doing Business (Registering Property).
	RPP	Registering Property – Procedures	Number of procedures	World Bank Doing Business (Registering Property).
Dependent	PA	Patent Application	Number/ Per Year	WIPO

Table A2. List of Countries by Income Group (2010–2023)

Income group	Countries
High-Income (31)	Australia, Austria, Belgium, Canada, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Iceland, Ireland, Israel, Italy, Japan, Korea (Rep.), Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Russian Federation, Saudi Arabia, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States
Upper-Middle-Income (21)	Argentina, Brazil, Bulgaria, China, Colombia, Costa Rica, Georgia, Indonesia, Jordan, Kazakhstan, Malaysia, Mexico, Montenegro, North Macedonia, Philippines, Romania, Serbia, South Africa, Thailand, Turkiye, Ukraine
Lower-Middle-Income (9)	Egypt (Arab Rep..), Honduras, India, Kenya, Kyrgyz Republic, Morocco, Tanzania, Uzbekistan, Viet Nam
Low-Income (4)	Burundi, Ethiopia, Madagascar, Rwanda,
Note: Income classifications based on World Bank (2023) GNI thresholds.	

Table A3: VIF details across Income group

Panel	Kept Proxes with VIF	Dropped Proxies
High	DCR(9.2), GEV(8.7), ATF(8.32), RDX(6.67), TRD(6.45), PCI(6.36), COI(6.12), KNC(5.84), HCI(5.84), IER(5.71), PSV(5.19), FSB(5.17), GPC(5.02), IND(4.82), SGC(4.71), SBS(4.55), TER(4.51), INT(4.37), KWS(4.25), TRT(4.13), SPT(3.91), CST(3.9), ICT(3.73), RPT(3.36), STG(3.25), TAX(2.97), GCF(2.97), MOB(2.95), BEV(2.84), INF(2.77), STA(2.74), HTE(2.63), GED(2.6), PMI(2.48), RPP(2.06), FDI(1.51), GGW(1.35), ELE(1.21)	EXP, ROL, GII, COC, RUQ, EBD
Upper-Middle	RDX(10.02), PCI(9.12), SBS(8.68), IND(8), INT(7.52), FSB(6.93), IER(6.36), COI(5.94), GCF(5.86), TAX(5.84), ROL(5.71), ATF(5.69), TRD(5.57), SPT(5.36), GEV(5.21), HTE(5.01), GPC(4.87), PMI(4.84), TRT(4.83), STG(4.41), PSV(4.39), RPP(4.37), CST(4.23), HCI(4.22), ICT(4.16), KWS(4.14), INF(3.81), ELE(3.79), GED(3.69), TER(3.49), FDI(2.98), RPT(2.97), BEV(2.85), SGC(2.46), MOB(2.2), GGW(1.54)	EXP, GII, STA, DCR, EBD, KNC, RUQ, COC
Low/Lower-Middle	GEV(9.68), GPC(9.18), IND(8.76), MOB(8.34), TAX(7.85), ATF(6.9), COC(6.85), TER(6.85), RUQ(6.78), ICT(6.65), FSB(6.2), INF(5.88), RPT(5.67), HCI(5.66), TRT(5.38), KNC(4.8), SGC(4.25), SPT(4.24), PSV(4.16), CST(3.8), COI(3.74), GED(3.58), GCF(3.43), KWS(2.94), STG(2.84), PMI(2.71), HTE(2.7), BEV(2.45), FDI(1.8), GGW(1.53)	EXP, TRD, PCI, ELE, GII, EBD, RPP, INT, ROL, SBS, DCR, STA, IER, RDX
Pooled (All)	GEV(10.08), ICT(9.77), FSB(9.56), INT(9.42), INF(8.84), KNC(7.16), SBS(6.86), KWS(6.38), RDX(6.25), ELE(5.99), GPC(5.81), PSV(5.14), COI(4.82), CST(4.23), TRT(3.82), TER(3.62), ATF(3.3), SPT(3.15), BEV(3.11), MOB(2.47), TRD(2.43), IND(2.35), PMI(2.21), TAX(2.19), GCF(1.94), HTE(1.82), STG(1.79), RPT(1.77), SGC(1.68), GED(1.62), RPP(1.33), GGW(1.3), FDI(1.24)	EXP, GII, ROL, PCI, COC, RUQ, HCI, EBD, DCR, IER, STA

Table A4: Cronbach Alpha

Determinant	alpha	k
ECON	.750	6
INVF	.724	5
INRD	.714	4
EDUC	.761	5

INFR	.942	7
REGB	.885	7
LEGL	.975	5
IPIO	.906	3
PROP	.828	2

Table A5: Diagnostic Tests for Autocorrelation and Heteroskedasticity

Panel	Wooldridge F-statistic	p-value	Modified Wald χ²	p-value	Diagnostic Outcome
High	8.94	0.004	189.35	0.000	Autocorrelation & Heteroskedasticity detected
Upper-Middle	10.12	0.003	142.71	0.000	Autocorrelation & Heteroskedasticity detected
Low/Lower-Middle	6.77	0.012	97.84	0.000	Autocorrelation & Heteroskedasticity detected
Pooled (All)	11.46	0.002	211.29	0.000	Autocorrelation & Heteroskedasticity detected

Table A6. Linear FE baseline results by income group (significance indicated at 1%, 5%, and 10% levels).

Determinant	High	Upper-Middle	Low/Lower-Middle	All-Income
ECON	GPC**, (–IND*)	(–GCF*), (–TRD*)	GPC*	–
INVF	–		–	–
INRD	RDX*	–	–	–
EDUC	KWS***	HCI**, KWS**	HCI*, TER*	–
INFR	(–ELE*)	FSB***, (–INT*)	ICT*	–
REGB	CST*	(–SPT**)	–	–
LEGL	GEV**	ROL***	–	–
IPIO	COI*	–	–	–
PROP	–	–	–	–

Table A7. Parsimonious PPML-FE (by Panel)

Determinant	High	Upper-Middle	Low/ Lower-Middle	Pooled (All)
ECON	GPC***, (–IND***)	GGW***, (–TRD***)	(–GCF**)	GPC**, (–IND***)
INVF	TAX***, DCR***, (-FDI***)	ATF***, TAX**	ATF***, (-TAX***)	ATF***, (-FDI***), (-SGC***), (-TAX**)
INRD	KNC***, HTE*	RDX***	(–KNC***)	RDX**, HTE*
EDUC	KWS**, (–HCI**)	TER***, KWS***	TER***, (–STG***)	TER***, KWS***
INFR	(–MOB***), (–ELE***), (–PCI***), (–INF*)	MOB***, INF**	(–INF***)	ELE***, INT***
REGB	SBS***, CST***, SPT**	(–SBS***)	PMI*, (-SPT*)	TRT***, (-BEV*)
LEGL	GEV***	(–PSV***)	COC***	GEV***
IPIO	(–IER***),	(–COI***)	COI***	–
PROP	–	RPT***, (–RPP**)	–	RPT**
*Note. *** p < 0.01; ** p < 0.05; * p < 0.10.*				

Table A8: Temporal Subsample PPML-FE Results (2010–2016 vs 2017–2023)

Determinant	High		Upper-Middle		Low/Lower-Middle		Pooled (All)	
	Period 1	Period2	Period 1	Period2	Period 1	Period2	Period 1	Period2
ECON	GPC***	GPC***	GDP**	GGW**		CFC**	GPC***, (-IND***)	IND**, (-GPC***)
INVF	(-FDI***	DCR***, (-FDI***)	TAX**, ATF**		ATF***, (-TAX***)	(-TAX***)	ATF***, (-FDI***)	(-FDI***), (-SGC**), (-TAX**)
INRD	KNC**, (-HTE**)	--	RDX***				RDX***	HTE*
EDUC	---	--	TER***, KWS***			(-STG***)	KWS**, TER***	KWS**, (-TER*)
INFR	(-PCI***), (-ELE**)	ELE**, (-PCI***), (-MOB*), (-INF*)	INF***, FSB***, (-ICT***)	(-FSB**)		(-INF***)	INT*, (-ELE***)	ELE***, INT**
REGB	CST***, SBS**	SPT***, SBS**, (-CST*)	CST*, (-SBS***)		PMI***, (-SPT**)	(-SPT*)	TRT*, (-BEV***)	BEV***

LEGL		GEV***		(-PSV***)		COC***		GEV***
IPIO	(-IER***)	(-IER***)	(-COI***)		COI***	COI***		
PROP			RPT*, (-RPP***)				RPT**	RTP**
Note. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.								

Table A9. PPML-FE (natural units) significant coefficients by p-value tier; clustered by country

Determinant	High	Upper-Middle	Low/Lower-Middle	Pooled (All)
ECON	GPC***, (–IND***)	GGW***, (–TRD**)	GGW**, (–GCF**)	GPC**, (–IND***)
INVF	TAX***, DCR**, (–FDI***)	ATF***, TAX***	ATF***, (–TAX***)	ATF***, (–FDI***), (-SGC***), (–TAX**)
INRD	KNC***, HTE**	RDX***	(–KNC***)	RDX**, HTE*
EDUC	KWS***, (–HCI**)	TER***, KWS***	TER***, (–STG***)	TER***, KWS***
INFR	(–MOB***), (-ELE***), (–PCI**), (–INF**)	INF**, MOB*, (-FSB**), (-ICT**)	(–INF***)	ELE***, INT***,
REGB	SBS***, CST***, SPT**, (–PMI**)	(–SBS***), (-CST**)	PMI***, (–SPT***)	TRT***, (–BEV**)
LEGL	GEV***	(–PSV***)	COC***	GEV***
IPIO	(–IER***)	(–COI***)	COI***	–
PROP	–	RPT***, (–RPP*)	–	RPT*
Note. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.				

Table A10. Robustness Validation of PPML-FE Proxies (LOCO and WCB Tests, 2010–2023)

Income Group	LOCO-Stable Proxies	LOCO-Sensitive (Excluded)	WCB Robustness
High-Income	GEV, IER, IND, SBS, CST, TAX, ELE	DCR, PCI, KNC, HCI, KWS, SPT, MOB, INF, HTE, PMI, FDI, RPP	None robust
Upper-Middle-Income	GGW, TAX, ATF, RDX, TER	TRD, FSB, ICT, INF, SBS, CST, PSV, COI, RPT, MOB, RPP, KWS	None robust
Lower-Middle / Low-Income	COI	GGW, GCF, TAX, ATF, KNC, STG, TER, INF, SPT, PMI, COC	None robust
Pooled (All)	GEV, INT, TRT, TER, ATF, IND, SGC	ELE, RDX, GPC_3, KWS, TAX, BEV, FDI, RPT, HTE	None robust

Note: This table reports results specifically from two robustness tests conducted on the PPML-FE models (2010–2023):

- Leave-One-Country-Out (LOCO) Stability Test – sequential exclusion of each country to assess coefficient sensitivity and persistence of significance.
- Wild-Cluster Bootstrap-t (WCB) – 1,000 replications with clustering by country, to validate inference under potential small-cluster bias.
- LOCO-Stable Determinants: Variables that retained sign and significance ($p < 0.10$) across all LOCO iterations.
- LOCO-Sensitive (Excluded): Variables significant in baseline PPML-FE but lost stability or changed sign in at least one LOCO iteration.
- WCB Robustness: None of the determinants passed the WCB robustness threshold (p_boottest < 0.10).