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THE HETEROGENEOUS CAUSALITY BETWEEN ECONOMIC FREEDOM AND INNOVATION: A PANEL DATA ANALYSIS ACROSS INCOME GROUPS

Tuğba ORTAY BAYKAL
Ph.D.
Istanbul Ticaret University
tugbaortaygokce@gmail.com
0009-0001-1414-2523

Elif GÜNEREN GENÇ
Professor
Istanbul Ticaret University
elifg@ticaret.edu.tr
0000-0001-5439-914X

ABSTRACT

This study investigates the bidirectional causality between economic freedom and innovation across 116 countries classified by World Bank income thresholds over the period 2013-2025. Employing second-generation panel data techniques that account for cross-sectional dependence, including the Pesaran CD test, CADF/CIPS unit root tests, and Dumitrescu-Hurlin panel Granger causality tests, we uncover striking heterogeneity in causal relationships across income groups. For high-income and upper-middle-income economies, innovation Granger-causes economic freedom, suggesting that technological advancement drives institutional reform and market liberalization. Conversely, for lower-middle-income and low-income economies, economic freedom Granger-causes innovation, indicating that institutional foundations must precede innovation capacity building. These findings carry important policy implications: developed nations should prioritize innovation ecosystems to catalyze further economic liberalization, while developing nations should focus on institutional reforms to enable innovation emergence.

Keywords: Economic freedom; Innovation; Panel Granger causality; Dumitrescu-Hurlin test; Income heterogeneity; Cross-sectional dependence.

JEL Classification: O30, O43, P14, C33

1. INTRODUCTION

Innovation and economic freedom constitute two fundamental pillars of sustainable economic development, yet the causal relationship between them remains contested in the literature (Doucouliagos & Ulubasoglu, 2006; Zhu et al., 2024). Economic freedom - encompassing property rights protection, regulatory efficiency, trade openness, and market accessibility - has long been theorized as a prerequisite for entrepreneurship and technological progress (Hayek, 1945; North, 1990). The logic is compelling: secure property rights incentivize long-term investment in research and development, while competitive markets reward innovative firms and punish inefficient incumbents (Acemoglu & Johnson, 2005). Simultaneously, an emerging body of scholarship suggests that the causal arrow may also point in the reverse direction, with innovation and technological advancement creating pressures for institutional reform, market liberalization, and the dismantling of regulatory barriers (Acemoglu et al., 2005; Murphy et al., 1991).

The question of causality between economic freedom and innovation carries profound policy implications. If economic freedom drives innovation, developing countries should prioritize institutional reforms - strengthening property rights, reducing regulatory burdens, and opening markets - as prerequisites for technological catch-up. Conversely, if innovation drives institutional improvement, investment in research capacity, human capital, and technology adoption may generate endogenous pressures for economic liberalization. The policy stakes are substantial: misidentifying the causal direction risks misallocating scarce development resources and pursuing reform sequences that may prove ineffective or even counterproductive (Bate et al., 2023).

Despite extensive research on the freedom-innovation nexus, three critical gaps persist in the literature. First, the existing empirical work predominantly assumes unidirectional causality, examining either how economic freedom affects innovation (Zhu & Zhu, 2017; Boudreaux, 2016) or how technological change influences institutions (Feldmann et al., 2019), but rarely testing systematically for bidirectional relationships. Second, most studies implicitly assume that the freedom-innovation relationship operates uniformly across countries at different development stages - an assumption increasingly challenged by evidence of income-level heterogeneity (Hu & Png, 2013; Liu & Feng, 2023). Third, first-generation panel econometric techniques remain prevalent despite overwhelming evidence that international macroeconomic data exhibit strong cross-sectional dependence, rendering conventional estimators biased and inconsistent (Pesaran, 2004, 2007).

This study addresses these gaps by employing second-generation panel econometric techniques to test for heterogeneous bidirectional causality between economic freedom and innovation across 116 countries, classified into four World Bank income groups, over the period 2013-2025. Our methodological approach comprises four stages: testing for cross-sectional dependence using the Pesaran (2004) CD test, conducting panel unit root tests robust to such dependence using the CADF/CIPS procedure (Pesaran, 2007), implementing the Dumitrescu-Hurlin (2012) heterogeneous panel Granger causality test that allows for country-specific causal coefficients.

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Our principal finding reveals a striking reversal in causal direction across income groups. For high-income and upper-middle-income economies, innovation Granger-causes economic freedom, consistent with theories that technological advancement generates constituencies demanding institutional reform and market liberalization. Conversely, for lower-middle-income and low-income economies, economic freedom Granger-causes innovation, suggesting that institutional foundations represent binding constraints that must be established before innovation can flourish. This heterogeneity implies that optimal policy sequencing differs fundamentally across development stages - a proposition with profound implications for development strategy.

The contributions of this study are threefold. First, we provide the first systematic test of bidirectional causality between economic freedom and innovation that allows causal direction to vary across income groups, moving beyond the unidirectional assumptions that characterize most prior work. Second, we employ second-generation panel techniques appropriate for international data exhibiting cross-sectional dependence, addressing methodological limitations that may have biased earlier findings. Third, our results offer actionable policy guidance: developed nations should prioritize innovation ecosystems to catalyze further institutional improvement, while developing nations should focus on establishing economic freedom fundamentals as prerequisites for innovation emergence.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical and empirical literature on the freedom-innovation nexus. Section 3 describes our data sources and variable construction. Section 4 details our econometric methodology. Section 5 presents the empirical results, and Section 6 concludes.

2. LITERATURE REVIEW

The theoretical foundations linking economic freedom to innovation derive from multiple intellectual traditions. Schumpeter (1942) established the foundational concept of "creative destruction," arguing that innovation emerges from entrepreneurs who disrupt existing market structures through novel products, processes, and organizational forms. This process requires institutional environments that permit market entry, tolerate failure, and reward success. Building on this foundation, Baumol (1990) demonstrated that the total supply of entrepreneurial talent in an economy is relatively fixed, but its allocation between productive activities (innovation) and unproductive activities (rent-seeking) depends critically on institutional incentives. When economic freedom is constrained, talented individuals redirect efforts toward capturing existing wealth rather than creating new value.

The Austrian school of economics provides complementary insights. Hayek (1945) emphasized that decentralized market mechanisms generate the price signals and competitive pressures necessary for entrepreneurial discovery. When economic actors possess freedom to pursue profit opportunities, they are incentivized to develop novel solutions to market problems. Kirzner (1973) extended this perspective by characterizing entrepreneurs as alert individuals who discover and exploit previously unnoticed opportunities, a process that requires freedom from regulatory barriers and secure property rights to function effectively.

Endogenous growth theory formalizes these insights within a macroeconomic framework. Romer (1990) demonstrated that technological progress emerges from intentional investment in research and development, with the returns to such investment depending on market size and appropriability conditions. Aghion and Howitt (1992) developed a Schumpeterian growth model in which innovation incentives depend on the expected profits from successful innovation net of entry costs-both directly influenced by economic freedom. Furman, Porter, and Stern (2002) synthesized these perspectives through their concept of "national innovative capacity," positioning institutional factors, particularly intellectual property protection and trade openness, as fundamental infrastructure that conditions how R&D inputs translate into innovative outputs.

Several mechanisms link economic freedom to innovation. Property rights protection constitutes the foundational channel. North (1990) demonstrated that secure property rights reduce appropriability concerns that might otherwise deter long-term investment in research and development. When inventors cannot capture returns from their innovations, incentives for inventive activity collapse. Acemoglu and Johnson (2005) provide causal evidence that property rights institutions exert substantial positive effects on long-run economic performance, operating partly through their impact on innovation incentives. Hall and Jones (1999) similarly show that differences in capital accumulation, productivity, and output per worker are fundamentally driven by differences in institutions and government policies.

The legal system's quality and origin matter substantially. La Porta et al. (1999) document that countries with common law legal origins exhibit stronger investor protections and more developed financial markets, facilitating innovation financing. Hu and Png (2013) develop this perspective by constructing an "Effective Patent Rights Index" capturing both statutory patent law and actual enforcement capacity. They demonstrate that growth-promoting effects of patent rights in patent-intensive industries depend crucially on institutional enforcement capacity-highlighting the complementarity between formal rules and functional institutions.

Regulatory efficiency and market openness operate as direct transmission channels. Zhu and Zhu (2017) document strong positive relationships between economic freedom and corporate patenting outcomes across 5,809 firms in 29 countries, linking sound regulation, limited government intervention, and open markets to innovation performance. Frictionless market entry and predictable regulatory environments reduce innovation costs while expanding market rewards for technological advancement. Boudreaux (2016) provides cross-country evidence that institutional quality-measured through rule of law, regulatory burden, and market openness-significantly predicts innovation outcomes even after controlling for income levels.

A complementary theoretical perspective suggests that causality may also run from innovation to institutional quality. Technological change creates new economic actors and interest groups who demand institutional reforms to protect and extend their activities. The emergence of knowledge-intensive industries generates constituencies favoring property rights protection, regulatory transparency, and trade liberalization. Acemoglu et al. (2005) theorize that technological change can shift

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political power toward groups favoring inclusive institutions. When innovation-driven economic growth creates a prosperous middle class dependent on continued technological progress, these groups pressure for institutional arrangements supporting further innovation. Murphy, Shleifer, and Vishny (1991) argue that innovative activities crowd out rent-seeking when returns to productive activities increase, leading endogenously to institutional improvements reinforcing market-oriented reforms.

Historical evidence supports this reverse channel. The Industrial Revolution in Britain was associated with significant institutional reforms, including extensions of property rights and dismantling of guild restrictions that had previously constrained technological adoption. More recently, the rise of technology sectors has been associated with deregulatory pressures in telecommunications, finance, and transportation across developed economies. Mokyr (2002) documents how technological change in Europe created new interest groups that successfully lobbied for institutional reforms protecting their activities.

2.1. Empirical Evidence and Research Gaps

The empirical literature provides substantial evidence of positive associations between economic freedom and innovation, though with important methodological variations. Table A (below) summarizes key empirical studies. Doucouliagos and Ulubasoglu (2006), in a comprehensive meta-analysis synthesizing 52 studies and over 6,400 observations, document weighted average partial correlations between economic freedom and economic growth ranging from +0.23 to +0.28 in best-practice specifications. Critically, their meta-regression detects specification bias: studies omitting physical capital inflate freedom-growth estimates, and panel designs yield smaller estimates than cross-sectional analyses.

Among the strongest identification strategies, Hu and Png (2013) employ the Rajan-Zingales cross-industry cross-country approach across 54 manufacturing industries in 72 countries. By interacting effective patent rights with industry patent intensity while controlling for country and industry fixed effects, this design addresses many confounding concerns. Furman, Porter, and Stern (2002) provide foundational OECD panel evidence using 3-year lags between inputs and patent outputs, establishing that intellectual property protection, trade openness, and R&D funding significantly predict international patenting rates.

Recent panel studies offer increasingly rigorous evidence. Ahmed et al. (2024), applying fixed effects and system GMM to 61 developing countries, find no statistically significant direct relationship between democracy and innovation, reinforcing the interpretation that governance influences innovation through economic freedom rather than directly through political institutions. Zhu, Yang, and Chu (2024), employing two-way fixed effects across 112 economies, identify economic freedom as a mediator between good governance and innovation outcomes. Brkic, Gradojevic, and Ignjatijevic (2020), applying system GMM to 43 European countries, find that changes in economic freedom, rather than levels alone, drive growth outcomes.

A critical limitation pervades much of the existing literature: the implicit assumption that the freedom-innovation relationship operates uniformly across development stages. Accumulating evidence suggests this assumption is untenable. Rodrik, Subramanian, and Trebbi (2004) demonstrate that institutions matter differently across development contexts, with the "rules of the game" varying in importance depending on a country's position in the global economy. Hu and Png (2013) provide compelling evidence through triple interaction analysis (effective patent rights × industry patent intensity × GDP per capita), demonstrating that growth-promoting effects of patent rights in patent-intensive industries are significantly stronger in higher-income countries. This suggests benefits of strengthening intellectual property protection are contingent on having complementary institutions, human capital, and market conditions more prevalent in advanced economies.

Liu and Feng (2023) provide direct evidence of heterogeneity in the freedom-innovation-productivity nexus, finding that economic freedom exhibits stronger effects on green total-factor productivity in high-income settings, while innovation matters more for middle-income countries. They report a negative freedom-innovation interaction in global and middle-income panels, suggesting complex threshold effects varying with development context. Bate, Wachira, and Danka (2023) extend this analysis by identifying differentiated bottlenecks across development levels using Global Innovation Index pillars. In lower-middle-income countries, human capital for R&D emerges as the primary constraint, followed by innovation linkages and knowledge absorption. In upper-middle-income countries, both R&D capacity and innovation linkages equally constrain innovation. In high-income countries, innovation linkages remain the main challenge even after basic R&D capacity is established. In lower-income contexts, innovation performance appears more strongly linked to enabling factors preceding market liberalization. Niazi (2025) finds that e-participation and democracy significantly predict Global Innovation Index scores in 86 Global South countries, while economic freedom does not emerge as significant in isolation-suggesting basic governance prerequisites may dominate in these settings.

Despite these contributions, several gaps remain. First, existing literature largely assumes unidirectional causality, rarely testing systematically for bidirectional relationships that may vary across development contexts. Second, studies predominantly rely on subgroup analyses or interaction terms rather than formal causality testing frameworks distinguishing correlation from predictive causation. Third, first-generation panel techniques remain prevalent despite evidence that international macroeconomic data exhibit strong cross-sectional dependence rendering conventional estimators biased and inconsistent (Pesaran, 2004, 2007). Fourth, heterogeneous panel causality methods permitting country-specific dynamics, such as the Dumitrescu and Hurlin (2012) test, have not been systematically applied to examine whether causal direction reverses across income groups.

Building on these foundations, we advance three hypotheses. First, we hypothesize that innovation Granger-causes economic freedom in high-income economies, reflecting the channel whereby technological advancement generates constituencies demanding institutional reform. Second, we hypothesize that economic freedom Granger-causes innovation in low-income economies, consis-

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tent with theories that weak institutions represent binding constraints requiring remediation before innovation can emerge. Third, we expect middle-income economies to exhibit transitional patterns, with upper-middle-income countries displaying innovation-driven dynamics while lower-middle-income countries remain constrained by institutional prerequisites.

3. DATA AND VARIABLES

Our analysis employs two primary variables measured annually from 2013 to 2025 across 116 countries.

Global Innovation Index (INN): We utilize the Global Innovation Index published by the World Intellectual Property Organization (WIPO) in partnership with INSEAD and Cornell University. Data were obtained from TheGlobalEconomy.com, a comprehensive database that aggregates official statistics from primary institutional sources and is widely used in academic research.The GII is a composite index ranging from 0 to 100 that captures the multi-dimensional facets of innovation through approximately 80 indicators organized into seven pillars: institutions, human capital and research, infrastructure, market sophistication, business sophistication, knowledge and technology outputs, and creative outputs. The index represents the most comprehensive and widely-used measure of national innovation capacity.

Index of Economic Freedom (FRE): We employ the Index of Economic Freedom published annually by The Heritage Foundation in partnership with The Wall Street Journal. This composite index, also scaled 0-100, measures economic freedom across 12 components grouped into four categories: rule of law (property rights, judicial effectiveness, government integrity), government size (tax burden, government spending, fiscal health), regulatory efficiency (business freedom, labor freedom, monetary freedom), and market openness (trade freedom, investment freedom, financial freedom).

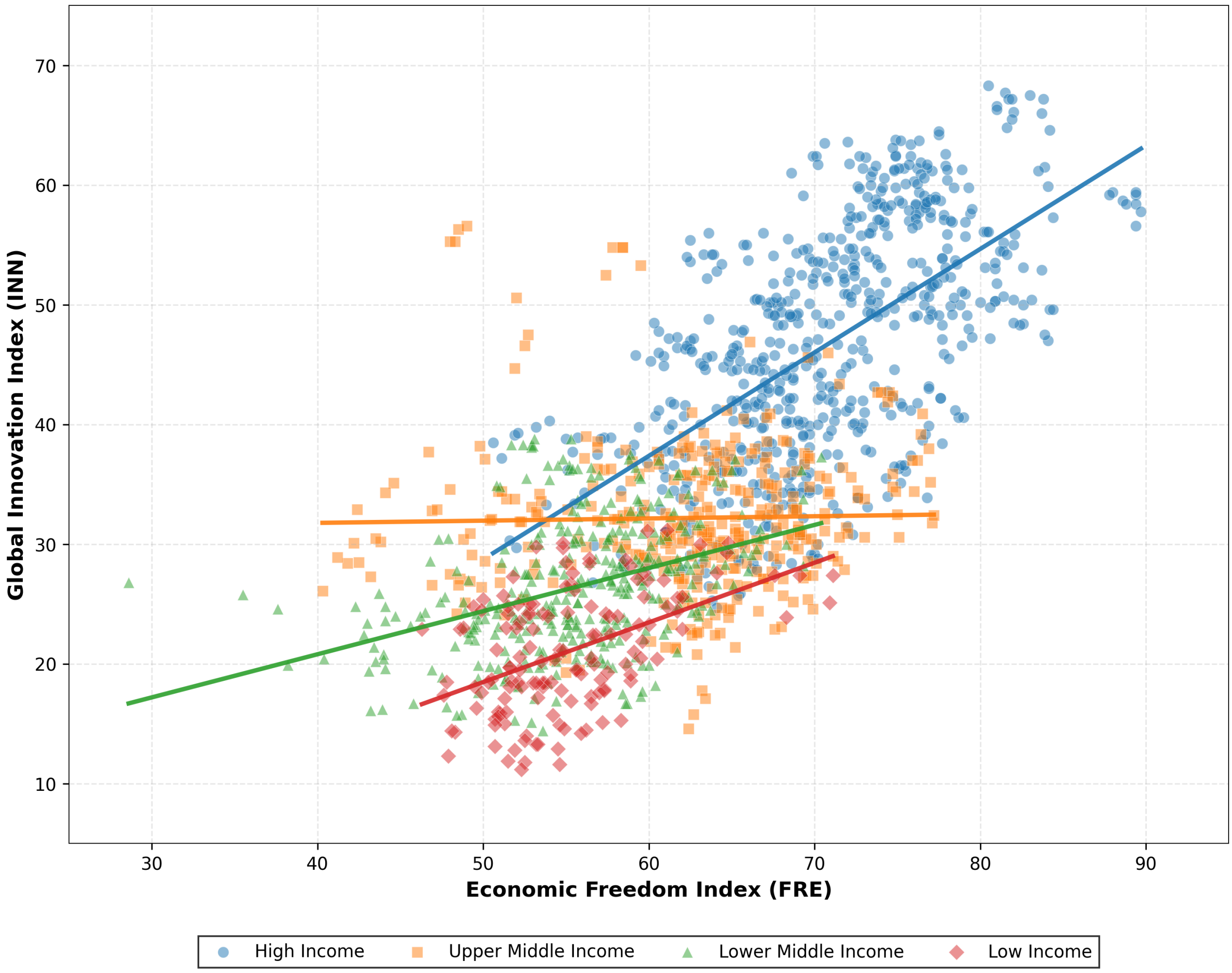
3.1. Country Classification

Countries are classified according to the World Bank's income group thresholds based on Gross National Income (GNI) per capita, using end-of-period (2025) classification to ensure consistency across the sample. We employ the following classification: High-Income Economies (GNI per capita ≥ $13,935), Upper-Middle-Income Economies (GNI per capita ranging from $4,496 to $13,934), Lower-Middle-Income Economies (GNI per capita ranging from $1,136 to $4,495), and Low-Income Economies (GNI per capita ≤ $1,135). Table 1 presents the country composition of each income group.

The resulting panel is strongly balanced, with all countries having complete observations for both variables across all 13 years (2013-2025), ensuring the validity of the Dumitrescu-Hurlin test assumptions.

3.2. Sample Characteristics

Table 2 presents descriptive statistics for both variables across income groups. Several patterns emerge. First, both innovation and economic freedom exhibit a clear positive gradient with income level, with high-income economies averaging 46.67 on the innovation index compared to 21.06 for low-income economies. Second, the dispersion in innovation scores is larger for higher-income groups, reflecting the heterogeneity among developed nations in innovation performance. Third, economic freedom shows less variation across the lower income groups, with lower-middle and low-income economies exhibiting similar mean freedom scores of approximately 55 points. Notable within-group heterogeneity exists, particularly among high-income economies where innovation leaders (e.g., Switzerland, Singapore) coexist with less innovation-intensive economies (e.g., oil-exporting Gulf states), though the Dumitrescu-Hurlin test accommodates such heterogeneity through country-specific coefficients.



The figure provides a preliminary visualization of the relationship between economic freedom and innovation across income groups. Several patterns emerge from this scatter plot. First, there is a clear positive gradient whereby higher-income economies cluster in the upper-right quadrant, exhibiting both higher innovation scores and greater economic freedom. Second, the fitted trend lines reveal substantial heterogeneity in the freedom-innovation relationship across income groups. High-income economies display the steepest slope ($\beta = 0.86$), indicating that a one-point increase in economic freedom is associated with a 0.86-point increase in innovation. In contrast, upper-middle-income economies exhibit an essentially flat relationship ($\beta = 0.02$), suggesting no meaningful correlation between freedom and innovation levels within this group. Lower-middle-income and low-income economies show moderate positive slopes ($\beta = 0.36$ and $\beta = 0.50$, respectively). Third, the dispersion patterns differ markedly: high-income countries span a wide range on both indices, while lower-income groups cluster more narrowly, particularly on the economic freedom dimension. These preliminary visual patterns motivate the formal econometric analysis that follows, which tests whether these correlational differences translate into heterogeneous causal relationships.

4. ECONOMETRIC METHODOLOGY

Our empirical strategy follows a sequential four-step procedure specifically designed to address the econometric challenges inherent in international panel data analysis. As emphasized by Pesaran (2004), international macroeconomic variables typically exhibit strong cross-sectional dependence arising from globalization, common shocks, and spatial spillovers, rendering first-generation panel techniques invalid. We therefore adopt second-generation econometric methods throughout our analysis.

Cross-sectional dependence in panel data arises from unobserved common factors, spatial autocorrelation, and economic interdependence characteristic of the globalized economy. When the cross-sectional dimension (N) exceeds the time dimension (T), as is typical in international panels, conventional first-generation estimators produce biased and inconsistent results (Pesaran, 2004). Detecting such dependence is therefore a critical preliminary step.

We employ four complementary tests to ensure robust inference. The **Breusch-Pagan (1980) LM test** computes the sum of squared pairwise correlation coefficients:

$$\mathrm{LM} = \mathrm{T}\,\Sigma_{\mathrm{i=1}}{}^{\mathrm{N-1}}\,\Sigma_{\mathrm{j=i+1}}{}^{\mathrm{N}}\,\hat{\rho}_{\mathrm{ij}}{}^{2}$$

where $\hat{\rho}_{ij}$ denotes the sample correlation between residuals of units i and j. This statistic is asymptotically χ^2-distributed with N(N-1)/2 degrees of freedom under the null hypothesis of cross-sectional independence. However, the LM test is sensitive to panel size and may exhibit poor finite-sample properties when N is large relative to T.

The Pesaran (2004) scaled LM test addresses this limitation by standardizing the LM statistic. Additionally, we implement the bias-corrected scaled LM test proposed by Baltagi et al. (2012), which incorporates mean and variance corrections to improve performance when T is small.

For panels where N is large relative to T-precisely our empirical context-the Pesaran (2004) CD test is particularly appropriate. Under the null hypothesis of cross-sectional independence, the CD statistic is asymptotically standard normal distributed regardless of whether the panel is balanced or unbalanced, and exhibits superior finite-sample properties compared to the LM-based tests.

4.1. Second-Generation Panel Unit Root Testing

Conventional first-generation panel unit root tests (Levin-Lin-Chu, Im-Pesaran-Shin, Fisher-type tests) assume cross-sectional independence and produce severely biased results when this assumption is violated (Pesaran, 2007). Given the confirmation of cross-sectional dependence in our data, we employ the Cross-Sectionally Augmented Dickey-Fuller (CADF) test proposed by Pesaran (2006, 2007).

The CADF test accounts for cross-sectional dependence by augmenting the standard ADF regression with cross-sectional averages of lagged levels and first differences of the individual series. These cross-sectional averages serve as proxies for the unobserved common factors generating cross-sectional dependence. The CADF regression specification for unit i is:

$$\Delta Y_{it} = \alpha_i + \rho_i Y_{i,t-1} + d_0 \bar{Y}_{t-1} + d_1 \Delta \bar{Y}_t + \varepsilon_{it}$$

where $\bar{Y}_t = (1/N)\ \Sigma_{i=1}{}^{N}\ Y_{it}$ represents the cross-sectional average at time t. The inclusion of $\bar{Y}$t-1 and $\Delta\bar{Y}_t$ filters out the cross-sectional dependence induced by unobserved common factors, yielding consistent unit root tests even in the presence of strong factor structures.

The **Cross-Sectionally Augmented IPS (CIPS)** panel statistic is obtained by averaging individual CADF statistics across cross-sectional units:

$$\mathrm{CIPS} = (1/N)\ \Sigma_{i=1}{}^{N}\ \mathrm{CADF}_i$$

where CADFi denotes the individual CADF t-statistic for unit i. Critical values for the CIPS statistic are tabulated in Pesaran (2007) for panels with constant only and constant-plus-trend specifications. The CIPS test has good size and power properties even with small T and moderate N, making it well-suited to our empirical context.

4.2. Panel Granger Causality Testing

We employ the **Dumitrescu and Hurlin (2012)** panel Granger causality test, which represents the state-of-the-art methodology for testing causal relationships in heterogeneous panels with cross-sectional dependence. Unlike the Holtz-Eakin et al. (1988) test that imposes homogeneous coefficients across units, the Dumitrescu-Hurlin (DH) test allows for heterogeneity in all parameters while providing valid inference under both cross-sectional dependence and unit root processes.

The underlying regression model for unit i is:

$$y_{it} = \alpha_i + \Sigma_{k=1}{}^{k}\ \gamma_i{}^{(k)}\ y_{i,t-k} + \Sigma_{k=1}{}^{k}\ \beta_i{}^{(k)}\ x_{i,t-k} + \varepsilon_{it}$$

where α_i represents country-specific intercepts, $\gamma_i{}^{(k)}$ are country-specific autoregressive coefficients, and $\beta_i{}^{(k)}$ are country-specific causal coefficients capturing the effect of variable x on y. The lag length K is assumed identical across countries but can be determined using information criteria.

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The null hypothesis of **Homogeneous Non-Causality (HNC)** states that x does not Granger-cause y for any cross-sectional unit:

$$H_0: \beta_i^{(1)} = \beta_i^{(2)} = \dots = \beta_i^{(k)} = 0 \quad \forall i = 1, 2, \dots, N$$

against the alternative that x Granger-causes y for at least some countries. The test statistic is computed as the average of individual Wald statistics across cross-sectional units:

$$\bar{W}^{HNC}_{N,T} = (1/N)\, \Sigma_{i=1}^{N} W_{i,T}$$

where Wi,T is the individual Wald statistic from testing $\beta_i^{(1)} = \dots = \beta_i^{(k)} = 0$ for country i. Under the null hypothesis, Dumitrescu and Hurlin (2012) derive standardized test statistics that follow a standard normal distribution asymptotically. Accordingly, the test conveys the strength of the causal evidence through these standardized Z-statistics rather than through a single pooled slope coefficient; comparisons of the relative strength of causality across income groups reported below are therefore based on the magnitude of these Z-statistics.

A key advantage of the DH test is its explicit accommodation of **coefficient heterogeneity**. The test allows $\beta_i^{(k)}$ to differ across countries, recognizing that the causal relationship between economic freedom and innovation may vary in magnitude-or even direction-across nations within each income group. The null hypothesis of homogeneous non-causality is rejected if there exists at least one country for which causality holds, providing a conservative test that avoids imposing implausible homogeneity restrictions on international data.

Methodological Considerations

Several features of the Dumitrescu-Hurlin test make it particularly appropriate for our analysis. First, unlike pooled estimators, the DH test permits *country-specific slope coefficients*, acknowledging that institutional and innovation dynamics differ across national contexts even within income groups.

Second, Monte Carlo simulations by Dumitrescu and Hurlin (2012) demonstrate that the test maintains correct size under various forms of *cross-sectional dependence*, including spatial correlation and common factor structures.

Third, the test remains valid when variables are I (1) provided they share the same integration order and are not cointegrated. When variables have *different integration orders*, alternative approaches such as the Emirmahmutoğlu and Köse (2011) test-which embeds unit root testing within the causality framework-may be employed.

Fourth, the test assumes a *balanced panel* with identical lag lengths across units. Our dataset satisfies this requirement through careful sample construction.

5. EMPIRICAL RESULTS

Table 3 presents the cross-sectional dependence test results for both variables across all four income groups. All four tests consistently reject the null hypothesis of cross-sectional independence at the 1% significance level for both variables in every income group. The Pesaran CD statistics are particularly large, ranging from 5.87 for economic freedom in the low-income group to 53.52 for innovation in the high-income group.

These results confirm the presence of significant cross-sectional dependence, likely arising from globalization-induced interdependencies, regional spillovers, and common global shocks affecting innovation and institutional quality. Given the confirmed presence of cross-sectional dependence, we proceed with second-generation unit root tests that account for this feature of the data.

Table 4 reports the CADF/CIPS panel unit root test results. For the innovation index (INN), we reject the null hypothesis of a unit root at conventional significance levels for high-income, lower-middle-income economies under both constant and constant-plus-trend specifications. Upper-middle-income economies show stationarity at the 10% level with constant only, while low-income economies show stationarity at the 10% level under the constant-plus-trend specification.

For economic freedom (FRE), the evidence is more mixed, with the null hypothesis not rejected for most groups under both specifications. This suggests potential non-stationarity in the freedom variable, a common finding in institutional variables that may exhibit high persistence. While the Dumitrescu-Hurlin test ideally requires variables at the same integration order, the test remains valid when both series share similar persistence characteristics and are not cointegrated (Dumitrescu & Hurlin, 2012). Nevertheless, this represents a limitation that future research could address using the Emirmahmutoğlu and Köse (2011) test, which accommodates variables with different integration orders.

5.1. Panel Granger Causality Test Results

Table 5 presents the Dumitrescu-Hurlin panel Granger causality test results, which constitute our central empirical findings. A striking pattern of heterogeneous causality emerges across income groups.

For high-income economies, the null hypothesis that innovation does not Granger-cause economic freedom is rejected (Z-stat = 2.996, $p < 0.10$), whereas the null that economic freedom does not Granger-cause innovation cannot be rejected (Z-stat = 0.026). There is therefore unidirectional Granger causality running from innovation to economic freedom (INN → FRE) in developed economies.

For upper-middle-income economies, the pattern is similar but stronger: there is unidirectional Granger causality running from innovation to economic freedom (Z-stat = 7.114, significant at the 10% level), while the reverse direction is not significant (Z-stat = 2.670). This suggests that as countries approach high-income status, innovation increasingly becomes the driver of institutional improvement rather than its consequence.

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The causality pattern reverses for lower-income groups. In lower-middle-income economies, there is unidirectional Granger causality running from economic freedom to innovation (Z-stat = 3.452, significant at the 10% level), while innovation does not significantly Granger-cause economic freedom (Z-stat = 2.489). The strongest evidence of Granger causality running from economic freedom to innovation appears in low-income economies, where the null is rejected at the 5% level (Z-stat = 7.328). This reversal provides empirical support for the hypothesis that institutional foundations serve as binding constraints in less developed economies, where basic economic freedoms must be established before innovation can emerge.

Taken together, these results reveal a clear development-stage pattern: the causal arrow runs from innovation to economic freedom in higher-income economies, but reverses direction in lower-income economies where economic freedom precedes innovation. This heterogeneity supports our theoretical framework suggesting that the freedom-innovation nexus operates differently across development levels.

6. CONCLUSION

This study has examined the bidirectional causal relationship between economic freedom and innovation across 116 countries classified by World Bank income groups over the period 2013-2025. Employing second-generation panel econometric techniques that account for cross-sectional dependence-including the Pesaran CD test, the CADF/CIPS unit root test, and the Dumitrescu-Hurlin heterogeneous panel causality test-we have uncovered a striking reversal in causal direction across development levels.

For high-income and upper-middle-income economies, we find that innovation Granger-causes economic freedom, consistent with theories of endogenous institutional change whereby technological progress generates new economic actors, industries, and interest groups that demand institutional reforms supporting knowledge-intensive activities. This innovation-to-freedom channel is statistically significant in both groups (Z-stat = 2.996 for high-income and 7.114 for upper-middle-income economies), indicating that as economies approach the high-income threshold, technological advancement becomes an increasingly robust driver of institutional reform.

Conversely, for lower-middle and low-income economies, the causality runs from economic freedom to innovation, indicating that institutional foundations represent binding constraints that must be relaxed before innovation can flourish. The stronger evidence for low-income economies (Z-stat = 7.328) relative to lower-middle-income economies (Z-stat = 3.452) further indicates that institutional reforms yield larger innovation dividends at the lowest development levels, where weak property rights, regulatory barriers, and limited market access constitute fundamental obstacles.

These findings carry significant policy implications. Optimal policy sequencing should differ across development stages: developing economies should prioritize establishing economic freedom fundamentals-securing property rights, reducing regulatory barriers, and opening markets-before investing heavily in innovation promotion. For developed economies, innovation ecosystems represent the primary policy lever, as investment in R&D, entrepreneurship support, and knowledge networks may generate positive institutional spillovers. For upper-middle-income economies, developing innovation capacity may help generate domestic constituencies for continued institutional reform, thereby avoiding the middle-income trap.

Several limitations warrant acknowledgment. First, Granger causality establishes predictive rather than structural causation; unobserved confounders affecting both variables with different lags could generate spurious findings. Second, our income group classification assigns countries based on contemporaneous income, though some countries may transition between groups over the sample period. Third, the relatively modest R^2 values, particularly for middle-income groups, indicate that other factors substantially influence these outcomes. Fourth, our sample period encompasses the COVID-19 pandemic (2020-2021), which may have induced structural breaks in both innovation activity and institutional dynamics.

Future research could extend this analysis by examining specific dimensions of economic freedom and innovation to identify which subcomponents drive the aggregate relationships, by investigating transition dynamics as countries move from freedom-constrained to innovation-driven development, and by explicitly testing for structural breaks to assess whether the identified causal patterns remained stable through periods of global disruption.

In an era of rapid technological change and global institutional convergence pressures, understanding the dynamic interplay between economic freedom and innovation remains crucial for sustainable development. Our findings contribute to both the literature on institutions and development and to policy debates regarding development strategy sequencing, underscoring that the relationship between economic institutions and technological progress is not universal but contingent upon development stage. Policy prescriptions that ignore this heterogeneity risk misallocation of reform effort and development resources.

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APPENDIX

Table 1. Country Classification by World Bank Income Groups

Income Group	Countries
High-Income Economies (N = 47)	Australia, Austria, Bahrain, Belgium, Canada, Chile, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Latvia, Lithuania, Luxembourg, Malta, Mauritius, Netherlands, New Zealand, Norway, Oman, Panama, Poland, Portugal, Qatar, Romania, Saudi Arabia, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, United States, Uruguay
Upper-Middle-Income Economies (N = 33)	Albania, Argentina, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominican Republic, Ecuador, Georgia, Guatemala, Indonesia, Iran, Jamaica, Jordan, Kazakhstan, Lebanon, Malaysia, Mexico, Montenegro, Namibia, Paraguay, Peru, Russia, Serbia, South Africa, Thailand, Turkey
Lower-Middle-Income Economies (N = 24)	Algeria, Bangladesh, Bolivia, Cambodia, Cameroon, Côte d'Ivoire, Egypt, El Salvador, Honduras, India, Kenya, Kyrgyzstan, Mongolia, Morocco, Nepal, Nigeria, Pakistan, Philippines, Senegal, Sri Lanka, Tunisia, Ukraine, Vietnam, Zambia
Low-Income Economies (N = 12)	Burkina Faso, Ethiopia, Guinea, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Tajikistan, Togo, Uganda

Note: *Classification based on World Bank GNI per capita thresholds (end-of-period, 2025). High-Income: GNI per capita ≥ $13,935; Upper-Middle-Income: $4,496-$13,934; Lower-Middle-Income: $1,136-$4,495; Low-Income: ≤ $1,135.*

Table 2. Descriptive Statistics by Income Group

Income Group	Var.	Obs.	Mean	Std. Dev.	Min	Max
High Income	INN	637	46.67	9.89	24.7	68.3
	FRE	637	70.50	6.90	50.6	89.7
Upper Middle Income	INN	364	32.19	6.45	14.6	56.6
	FRE	364	62.29	7.47	40.3	77.2
Lower Middle Income	INN	361	26.69	5.62	14.4	38.8
	FRE	361	55.47	5.83	28.6	70.4
Low Income	INN	140	21.06	4.99	11.2	31.2
	FRE	140	55.28	4.74	46.3	71.1

Note: *INN = Global Innovation Index; FRE = Index of Economic Freedom. Sample period: 2013-2025.*

Table 3. Cross-Sectional Dependence Test Results

Income Group	Test	INN	FRE
High Income	Breusch-Pagan LM	5848.17***	4241.93***
	Pesaran scaled LM	96.33***	63.21***
	Bias-corrected scaled LM	94.29***	61.17***
	Pesaran CD	53.52***	15.72***
Upper Middle Income	Breusch-Pagan LM	2695.31***	1307.39***
	Pesaran scaled LM	84.27***	33.81***
	Bias-corrected scaled LM	83.11***	32.63***
	Pesaran CD	37.71***	13.71***
Lower Middle Income	Breusch-Pagan LM	2645.41***	1166.97***
	Pesaran scaled LM	82.46***	28.69***
	Bias-corrected scaled LM	81.29***	27.52***
	Pesaran CD	41.42***	11.49***
Low Income	Breusch-Pagan LM	450.45***	154.82***
	Pesaran scaled LM	37.71***	9.51***
	Bias-corrected scaled LM	37.24***	9.06***
	Pesaran CD	20.68***	5.87***

Note: **** indicates significance at the 1% level. H_0: No cross-sectional dependence.*

Table 4. CADF/CIPS Panel Unit Root Test Results

		INN		FRE	
Income Group	**Statistic**	**Constant**	**Const.+Trend**	**Constant**	**Const.+Trend**
High Income	t-bar	-2.778***	-2.636***	-1.369	-1.916
	Z(t-bar)	-6.794	-2.372	2.255	2.167
Upper Middle Income	t-bar	-1.984*	-2.199	-2.249	-1.231
	Z(t-bar)	-1.271	0.287	0.050	2.354
Lower Middle Income	t-bar	-2.553***	-2.829***	-1.564	-2.044
	Z(t-bar)	-3.934	-2.640	0.735	1.004
Low Income	t-bar	-2.067	-2.726*	-1.284	-0.752
	Z(t-bar)	-1.024	-1.393	1.356	4.507

Note: ****, ** and * indicate significance at 1%, 5% and 10% levels. H_0: Panel contains unit roots.*

Table 5. Dumitrescu-Hurlin Panel Granger Causality Test Results

Income Group	Null Hypothesis	Z-Stat	Decision
High Income	INN does not homogeneously cause FRE	2.996*	Reject
	FRE does not homogeneously cause INN	0.026	Accept
Upper Middle Income	INN does not homogeneously cause FRE	7.114*	Reject
	FRE does not homogeneously cause INN	2.670	Accept
Lower Middle Income	INN does not homogeneously cause FRE	2.489	Accept
	FRE does not homogeneously cause INN	3.452*	Reject
Low Income	INN does not homogeneously cause FRE	2.330	Accept
	FRE does not homogeneously cause INN	7.328**	Reject

Note: ****, ** and * indicate significance at 1%, 5% and 10% levels respectively.*