ISSN 1833-1726
E-ISSN 3083-3825
https://taxpolicyjournal.org

Global innovation index as a predictor of future economic readiness: A cross-country forecasting analysis

LAOUAR Adbelhafid
University of Boumerdes, Boumerdes, Algeria
Corresponding Email: abdelhafidlaouar@univ-boumerdes.dz

FERZIZI Ibrahim
Higher School of Social Security, Mohamed Saleh Mentouri, Algiers, Algeria
Email: i.ferzizi@edu.esss.dz

How to Cite
LAOUAR, A., & FERZIZI, I. (2026). Global innovation index as a predictor of future economic readiness: A cross-country forecasting analysis. *Tax Policy Journal*, *22*(1), 48-73. https://taxpolicyjournal.org/index.php/tpj/article/view/18

Submitted: 18 January 2026 | Revised: 09 February 2026 | Accepted: 27 March 2026

Abstract---In this research paper, the predictive power of the Global Innovation Index (GII) is explored within the scope of using it as a tool of strategic foresight, as opposed to its common perception as a static comparative measure of the current state. The concept of the GII is redefined and interpreted as a tool that helps in predicting countries' future readiness for economic growth through innovation. A database with data from cross-sections of six benchmarking economies – Switzerland, the United States, Germany, China, India, and Algeria – is used to create an initial dataset containing the GII score, the Economic Complexity Index, the IMD Digital Competitiveness score, R&D spending, Human Capital Index, and internet penetration level. Based on descriptive statistics, correlations, and principal components analysis, the composite indicator of Future Economic Readiness (FERI) is developed. According to the results, high correlation exists between the index and economic complexity, digital competitiveness, and R&D spending levels, while correlation with internet penetration is much lower. Limited by the sample size, generalization of results is impossible, and the next step would involve estimation via panel data econometrics. As such, policymakers need to focus on increasing investment in R&D and developing human capital resources as two innovation drivers highly correlated with future economic readiness, with the lowest performing economies gaining the most benefit from changes to their innovation ecosystems. Novelty of this work is due to the use of the GII as an innovation foresight instrument and creation of the FERI indicator.
Keywords---Global Innovation Index, economic readiness, innovation forecasting, economic complexity, digital competitiveness.
JEL Classification: O30, O47, O57, C33, C53

1. Introduction

Within the modern global world, the potential for innovation has changed from being a marginal issue for advanced nations into a central driver of national economic competitiveness over time. With regard to how the world economy is evolving through the middle years of the 2020s, growth and resilience will be increasingly independent from countries' natural resource base but contingent on the consistent development, dissemination, and application of knowledge. This new trend, typically framed in terms of the knowledge economy, necessitates a radical rethink in how we gauge and predict the economic futures of our nation-states (OECD, 1996; Chen & Dahlman, 2006). This need for a radical rethink comes at a time when there have been massive innovations in technology under the industry 4.0 umbrella, the lingering effects of a highly disruptive global pandemic and the need to embark on both a green and digital transition across the globe. For policymakers, this presents the specific task of predicting future innovation capabilities rather than simply assessing present ones.

Knowledge economy developments have set a new definition of the criteria of success for nations. The digitization process does not only affect a certain industry, but it transforms the entire structure of industries, labor, and institutions (Brynjolfsson &

McAfee, 2014; OECD, 2019). Thus, readiness in the modern era is about more than financial security or physical structures; it is about the capacity of nations to utilize economic, digital, and human potential to prepare themselves for upcoming challenges and opportunities. Innovation should be seen as a means of predicting outcomes.

Since 2007, the Global Innovation Index (GII) has evolved to be the world's leading index and standard for the assessment of national innovation systems (WIPO, 2024). With its wide variety of indicators clustered into seven sub-pillars, the GII provides a holistic picture of institutional, human, infrastructural, and market factors contributing to knowledge creation and innovation activities. Despite its extensive usage, the analysis using the GII has mostly been applied in a descriptive manner: it has been referred to as an index that evaluates the current situation but not as one that forecasts future conditions of the economy (Dempere et al., 2023; Rajabov et al., 2023).

Analytically speaking, the time period of 2015-2025 can be considered quite a strategically critical period. The period includes the start and the mid-term stages of the implementation of the UN's Sustainable Development Goals, the increasing digitalization of the planet, and the high level of economic instability caused by the pandemic. Countries with advanced national innovation systems had greater chances to focus on the development of digital solutions and fast responses to problems related to healthcare, while those with weaker innovation potential had to face even bigger challenges and slower recovery rates (Vlasova & Saprykina, 2023). The current stage provides the necessary level of variance to examine the validity of the GII.

The core research problem considered in this paper is related to the absence of a rigorous country-comparative model that would turn the Global Innovation Index into a forward-looking tool rather than just a classification method. Most papers use GDP growth as the only indicator of development, which is an oversimplification because it does not reflect the necessary structural changes needed to be made by a country in order to remain competitive in the information economy. The paper offers a new index – the Future Economic Readiness Index (FERI) – which includes GDP growth, economic complexity, digital competitiveness, and institutions as its components. The change of focus on multi-horizon forecasting helps determine the main pillars of GII that signal changes in the economy.

Specifically, there are five key contributions to the respective scholarly literature of innovation economics and strategic foresight. First, the construction of the index called "Forwardness and Economic Readiness Index" is based on PCA of theoretically justified indicators of forwardness. Second, the Global Innovation Index is transformed into a tool of genuine strategic foresight through the analysis of multiple horizons in the lead-lag panel design. Third, the GII index is combined with additional benchmarks such as GKI, ECI, and DCI to explore synergy effects and mediating pathways (Hidalgo & Hausmann, 2009). Fourth, traditional regression approaches are compared to machine-learning forecasting algorithms for the purpose of determining which method is more efficient for strategic foresight at the national level (Mullainathan & Spiess, 2017). Finally, the analysis is conducted separately for developed and developing countries to highlight how the innovation-readiness relationship is affected by the development status (Vlasova & Saprykina, 2023; Cetinguc et al., 2023).

The structure of the rest of this paper will be as follows. In Section 2, the literature is identified with the particular research gaps that are being addressed. In Section 3, the research questions and objectives are stated. In Section 4, the theoretical model along with the formal hypotheses are developed. Section 5 provides a thematic review of the literature. Section 6 provides the details about the methodology used. Section 7 presents the empirical findings. The discussion, theory development, policy implications, limitations, future research directions, and conclusions are in Sections 8 through 12.

2. Research Gap

It is safe to say that even though there exists a fairly large amount of literature regarding innovation indicators and economic growth, it suffers from certain major flaws which hinder their utility in future planning and policymaking. This paper highlights six gaps in the existing literature on innovation economics.

The first gap is related to the presence of an overwhelming amount of cross-sectional analysis that is currently being done. Quite a few studies continue linking the GII index with current economic performance for one year only (Dempere et al., 2023; Rajabov et al., 2023). While such research provides evidence of the importance of innovation in contemporary times, there is a lack of recognition of the time-sensitive aspect of the index. Innovation by definition implies multiyear efforts with delayed economic results.

Secondly, it should be observed that there are few panel lag-lead frameworks that regard GII as a predictive tool. As of now, most empirical applications have relied on innovation indices as explanatory or control variables for growth models (Cetinguc et al., 2023). The absence of an examination on whether the GII score of 2018 predicts the economic state of 2023 means that GII is merely a descriptive scorecard.

Thirdly, the problem lies in the integration of indices that complement one another into an overall forecasting model. Most research tends to consider the aforementioned indices as separate units. However, from the point of view of endogenous growth and national innovation systems theory, all four indices mentioned above are inherently interlinked (Hidalgo & Hausmann, 2009; Brynjolfsson & McAfee, 2014).

Fourth, there is no such thing as a composite theoretical-dependent variable regarding future economic readiness. There is widespread use of gross domestic product per capita or gross domestic product growth rate as measures of economic performance. While these measures are significant, they are very narrow and fail to measure the qualitative changes that need to take place to meet the requirements of the knowledge economy.

Five, the literature fails to provide evidence of benchmarking in econometrics versus machine-learning forecasts for innovations across countries. Even though machine learning has been used in economics research (Mullainathan & Spiess, 2017), the use of machine learning in innovation readiness forecasting remains embryonic (Unanoglu & Ozari, 2024). Econometrics models have the ability to draw causal inferences, but they face challenges with the non-linearity associated with international data; on the other hand, machine learning models might produce better results, but they can be opaque.

Moreover, there is still insufficient differentiation regarding the relationship between GII-readiness across different income levels and geographic regions. Emerging markets have different institutional challenges and take different innovation paths compared to the developed countries (Vlasova & Saprykina, 2023). The pooled estimations can mask certain differences. This research will address all six shortcomings mentioned above through the development of the FERI, including GII into a dynamic panel data forecasting approach, using additional indexes, comparing traditional econometrics approaches to machine learning models, and differentiating the sample.

3. Research Questions and Objectives

3.1 Research Questions

- RQ1: To what extent does the GII overall score possess predictive power for a country's FERI at one-, three-, and five-year horizons?
- RQ2: Which GII sub-pillars exert the strongest differential predictive effects on future economic readiness?
- RQ3: Does the predictive significance of the GII persist after controlling for the GKI, ECI, DCI, R&D expenditure, human capital, ICT infrastructure, FDI, and institutional quality?
- RQ4: Do machine-learning forecasting models provide significantly higher out-of-sample accuracy compared to panel econometric models?
- RQ5: How does the predictive relationship between innovation and economic readiness vary between developed and emerging economies?

3.2 Research Objectives

1. O1: Construct the FERI using PCA applied to eight forward-looking economic indicators across approximately 130 countries for the period 2015–2025.
2. O2: Assemble a cross-country panel dataset and estimate the lead-lag predictive power of GII total and pillar scores using pooled OLS, fixed-effects, and random-effects models.
3. O3: Estimate dynamic panel models (System-GMM) to account for endogeneity and persistence while integrating ECI, DCI, and GKI as complementary predictors.
4. O4: Benchmark the out-of-sample forecasting performance of Random Forest and Gradient Boosting algorithms against econometric benchmarks using RMSE, MAE, and R^2 on a 2021–2025 test set.
5. O5: Derive policy-relevant insights by identifying which innovation dimensions most effectively predict economic transformation in emerging versus developed economies.

4. Hypotheses Development

H1 — Overall GII Effect

Greater scores on the GII index are correlated with increased levels of future economic readiness (FERI) when the horizons of consideration are h = 1, 3, and 5 years ahead. Based on the theory of endogenous growth, the assumption is that continuous long-term economic growth is driven by active accumulation of knowledge and technology (Romer, 1990; Aghion & Howitt, 1992). The GII represents some of the key factors that contribute to innovation, such as investments in R&D activities, human resources, and institutions. Unlike simple correlations, readiness implies an inherent ability to evolve and thrive, which emerges as a result of a well-functioning national innovation system (Freeman, 1995; Johnson, 2010). This descriptive analysis serves as initial evidence to support the above-mentioned hypothesis, demonstrating co-variations between GII, ECI, and DCI values within the range of 16.2 to 67.5 in 2024.

H2 — Input Pillar Predictive Power

As far as GII input pillars are concerned, Human Capital and Research along with Business Sophistication have greater predicting power as compared to Infrastructure, Market Sophistication, and Institutions. Absorptive capacity of a country plays an important role in its being able to gain anything out of innovation (Cohen & Levinthal, 1990). Human capital and research provide the basis of understanding of new inventions and adoption of innovations (Lucas, 1988), whereas, business sophistication makes sure that innovations are adopted properly by the businesses. Knowledge Economy Theory highlights that human capital and sophistication of firms play an essential part in change rather than infrastructure alone (OECD, 1996; Chen & Dahlman, 2006).

H3 — Output Pillar Predictive Power

Of all the output-related pillars in GII, knowledge and technology outputs appear to have the best predictive capabilities regarding economic preparedness in the future. The tangible signs of innovation capacity include such measures as patents, high-technology manufacturing, and software exports. As per the Schumpeterian model of creative destruction, technological output is responsible for breaking down existing industrial structures and allowing the establishment of new growth periods (Aghion & Howitt, 1992). Recent studies indicate that technological outputs play a more significant role in driving export intensity and GDP growth compared to creative or institutional outputs (Tkachenko & Chornyi, 2025; Araujo et al., 2024).

H4 — Mediating Role of Complexity and Digital Competitiveness

The indicators of ECI and DCI might help to intensify the association between GII and FERI through improving the environment in which innovations are implemented to achieve future readiness. Innovations do not occur in a vacuum; on the contrary, their effect largely depends on the productive level and development of a digital environment within the economy. From the perspective of economic complexity theory, the productive space is believed to define the growth opportunities for an economy in the future (Hidalgo & Hausmann, 2009), whereas digital competitiveness is believed to be the bridge that allows innovations to spread fast and efficiently (Brynjolfsson & McAfee, 2014). The analysis of the indicators in the paper suggests that they develop concurrently, implying that indicators of ECI and DCI can further improve the effect of innovations on future readiness. The results obtained are in line with the conclusions by (Kiselakova et al, 2024) who found a significant correlation between innovation performance and digital competitiveness with structural equation modeling.

H5 — Heterogeneity Across Income Groups

The marginal impact of GII on prediction is higher in emerging economies compared to developed countries. The above statement is based on the technology catch-up model, according to which innovation in emerging economies is characterized by adaptation and utilization of global technological innovations, which leads to non-linear productivity jumps (Vandenbussche et al., 2006; Lee, 2013). Developed economies operate at the global technology frontier, and their marginal gains from innovations are incremental in nature. Algeria occupies the bottom positions in the distribution of all indices—GII 16.2 (2024), ECI -0.63 (2026), HCI 0.53 (2024).

H6 — Machine-Learning Forecasting Superiority

AI techniques such as machine learning models (Random Forest and Gradient Boosting), on the other hand, exhibit more robust out-of-sample forecast accuracy compared to benchmark models in econometrics. Predicting the state of the economy of any nation is quite difficult as there will be high dimensional data with non-linear relations and possibly even structural breaks. While econometric models may work well in estimating the average causality effect, they have the problem of being rigid on the functional form assumed (Mullainathan & Spiess, 2017). The random forest and gradient boosting machine learning models are designed to minimize errors in predictions through capturing complex relations without assuming distributions (Breiman, 2001; Friedman, 2001). Given the multi-faceted nature of the GII and the volatility of the 2015–2025 period, ensemble ML methods are expected to produce more robust out-of-sample forecasts (Unanoglu & Ozari, 2024).

5. Literature Review

5.1 Innovation, Productivity, and Endogenous Growth Theory

Innovation and its effect on economics can be explained based on endogenous growth theory. Romer (1990) and Lucas (1988) significantly changed the approach to the Solow (1956) growth model, making knowledge and technological change endogenously determined, being dependent on human capital and R&D. Innovation becomes a major factor for productivity growth according to this approach. Griliches (1992) and Hall et al. (2010) show that there are important gains from R&D both privately and socially. Benhabib & Spiegel (1994) prove that the quality of human capital determines income levels among countries, not just the amount of capital. A more recent study focuses on innovation return through the prism of positioning in international value chains (Dempere et al., 2023) and institutions (Acemoglu et al., 2005). One of the problems with the foundational theme discussed above is its general nature: the importance of innovation is shown but its specific varieties are usually ignored. This paper develops the idea, breaking down innovation into various components using GII indicators.

5.2 National Innovation Systems, Institutional Capacity, and Technology Catch-Up

As per the National Innovation Systems (NIS) model (Freeman, 1995; Nelson, 1993), innovation is not just the product of R&D but an intricate process of relationships among enterprises, universities, and other governmental entities. Quality of institutions, including protection of property rights, rule of law, stability of regulations, forms the basis of such systems (Acemoglu et al., 2005). In developing nations, the NIS concept becomes the means to achieve technology catching up (Lee, 2013). According to Vlasova and Saprykina (2023), even under turbulent conditions, countries with resilient NIS were capable of maintaining growth due to their robustness. In their empirical work, Cetinguc et al. (2023) reveal that level of human development and innovativeness are important factors that explain competitiveness among nations, especially non-OECD countries. However, research related to the NIS concept is mostly qualitative or employs static proxies of institutions, whereas this study employs the dynamic Institutions dimension of the GII lead-lag analysis.

5.3 Knowledge Economy, Human Capital, and Technological Readiness

Knowledge-based economy transition (OECD, 1996) has made human capital a driver of competitiveness from a mere factor of production. Technological readiness, as highlighted by Chen & Dahlman (2006), requires literacy and skills alongside information and communication technology (ICT) access. Barro and Lee (2013) and Hanushek and Woessmann (2015) Evidence for the connection between human capital and long-term economic growth exists in the literature. Human Capital Index (World Bank, 2024) operationalizes these dynamics on the national scale; in our dataset, this variable is between 0.49 (India) and 0.76 (Switzerland) – reflecting cross-country variability in the GII index (r=0.85). As an alternative measure, Global Knowledge Index (MBRF & UNDP, 2023) incorporates education, research, innovation, economy, and ICT into a complementary measurement approach. A lack of analysis exists regarding knowledge measures in relation to innovation measures in a dynamic perspective; this paper seeks to fill the gap using GKI as a complementary pillar of GII.

5.4 Economic Complexity, Productive Capabilities, and Long-Run Growth Forecasting

According to economic complexity theory (Hidalgo & Hausmann, 2009; Hausmann et al., 2014), what a country exports is crucial for determining its future growth path, not how much it exports. ECI captures knowledge embodied within productive structures; countries that export more complex goods are expected to have greater growth prospects than predicted by traditional income and institutional indicators. Tacchella et al. (2012) introduced complementary Fitness and Complexity indicators validating the predictive value of structural complexity. In their paper, Araujo et al. (2024) demonstrate that GII Business Sophistication and Infrastructure indicators are predictors of ECI values, indicating that investment in innovations results in productive complexity development. Within the current study, ECI is observed between –0.63 (Algeria) and 2.14 (Switzerland) and is correlated with the GII at 0.97, indicating strong structural similarities that require careful examination in terms of whether mediation or co-determination are involved. ECI has yet to be utilized systematically as a mediator in predicting country readiness using the GII.

5.5 Digital Transformation, Digital Competitiveness, and Economic Performance

Being in the 'Second Machine Age' (Brynjolfsson & McAfee, 2014), digital competitiveness has become an essential characteristic of being economically ready. According to the OECD (2019), digitalization affects the whole economy rather than ICT alone. The IMD Digital Competitiveness Ranking (IMD, 2024) shows how well the countries implement the use of digital technologies through knowledge, technology, and future readiness criteria. The importance of innovation performance as a significant factor affecting digital competitiveness is highlighted by studies such as those conducted by Kiselakova et al. (2024) and Sofrankova et al. (2022). This is additionally confirmed by the high association between the DCI and the GII (r = 0.97) in the six-country sample. The lack of Algeria on the ranking shows the difficulties associated with measuring countries that do not have sufficient digital infrastructure.

5.6 Strategic Foresight, Composite Indices, and Innovation Policy Forecasting

Strategic foresight entails the process of exploring possibilities for the future in order to support decision-making in the present (Miles et al., 2008; Popper, 2008). The composite indicators such as the GII have been extensively employed in policymaking through policy scoreboards, but are largely unused in foresight. According to Mullainathan and Spiess (2017), machine learning models are perfect for predictive tasks when prediction is the aim, not causal identification. The work of Unanoglu and Ozari (2024) shows the potential that the random forest algorithm has in predicting manufacturing value added based on GII dimensions, thereby providing the methodology foundation for this study in the cross-national FERI framework.

5.7 Methodological Critique of Prior Empirical Studies

There are also several issues with methodology as identified in the literature review. First, the 'index-to-GDP' relationship may suffer from endogeneity and reverse causality, as wealthier countries can invest more in innovation. While GMM panel models (Arellano & Bond, 1991; Blundell & Bond, 1998) have been developed to solve the endogeneity issue, their application may be limited due to the short time spans for which they can be used. The Global Innovation Index has also been criticized in relation to its weighting mechanism as well as the partially descriptive nature of certain sub-indicators (Cetinguc et al., 2023). Utilizing single-item measures for the dependent variable does not take into account the multidimensional nature of structural change in the knowledge economy.

6. Theoretical Framework and Conceptual Model

Five different theoretical perspectives are synthesized within this theoretical model. The first one is endogenous growth theory (Romer, 1990; Aghion & Howitt, 1992). This perspective presents an important mechanism for the model. According to the endogenous growth theory, R&D investments and human capital development create positive feedbacks through the production of externalities in terms of knowledge, which result in differences in growth rates between nations. Next, national innovation systems theory (Freeman, 1995) defines how the process of investment in knowledge and skills is organized at the institutional and social level. The third concept is knowledge economy theory (OECD, 1996; Chen & Dahlman, 2006), where human capital, intellectual property rights, and information infrastructure are identified as key intangible resources for future value generation. Fourthly, economic complexity theory (Hidalgo & Hausmann, 2009) is used to operationalize capability accumulation as a predictor of diversification and growth.

The causal pathway works as follows: The past performance of innovation of a country, measured by the GII at time t, is based on the input and output stock of innovations. These factors, through a national innovation system, provide spillover effects and capability development, which result in better economic readiness in the future at time t+h. This process is affected by economic complexity, digital competitiveness, and institutions. Country-specific and year-specific fixed effects account for unobservable differences across countries and years respectively. Interacting GII with a dummy variable capturing a developing economy will test the presence of heterogeneity, and thus, H5 will be tested.

7. Methodology

7.1 Research Design

The research uses a quantitative cross-country panel data methodology that combines explanation with econometric modeling and prediction with machine learning forecasting. The panel data method facilitates controlling for country-specific differences that are not observed by fixed effects and establishing causality by the use of lagged explanatory variables. The dynamic estimation technique (GMM System) deals with the time persistence of economic preparedness as well as potential endogenity (Arellano & Bond, 1991; Blundell & Bond, 1998). Machine learning is used to deal with the issue of forecasting using training and test datasets and rolling origin validation (Mullainathan & Spiess, 2017).

7.2 Sample, Data Sources, and Harmonization

The main sample consists of countries that appear regularly in at least eight out of eleven annual editions of the GII spanning from 2015 to 2025, resulting in a total number of around 100 to 130 countries. Countries will be coded by their three-character ISO 3166-1 alpha-3 codes, allowing reliable merging across data sources. For the purpose of the descriptive benchmarks in Section 8, a six-country cross-section is used. It consists of countries exhibiting all levels of the GII score, ranging from a leader in innovation at rank 67.5 (Switzerland) to a country within the lowest quintile of GII rankings (Algeria at rank 16.2).

Imputation of missing values less than 10 percent in each country-year cell is done through linear interpolation when values from adjacent years exist. The countries that have less than five valid GII scores are dropped. Continuous variables are standardize (z-scored) prior to running PCA and taken in logs for growth equations.

7.3 Dependent Variable: Future Economic Readiness Index (FERI)

FERI is generated by performing PCA using eight forward looking indicators at time t+h: (i) per capita GDP growth rate; (ii) high technology export intensity; (iii) DCI value; (iv) ECI; (v) net FDI inflows as % of GDP; (vi) human capital growth; (vii) ICT readiness (Internet access); and (viii) institutional quality (average of WB Governance

Indicators). Each indicator is normalized to have a mean of zero and standard deviation of one. Applicability for factor analysis is confirmed by computing KMO and Bartlett's tests. Principal components having eigenvalues greater than one are included in the model, as per the Kaiser criteria. The first principal component score rescaled between 0 and 100 generates the FERI value.

7.4 Independent and Control Variables

The primary predictor is the GII total score lagged by h years. Pillar-level models decompose this into the seven GII sub-pillar scores to identify differential effects (H2, H3). Control variables include the GKI, ECI, and DCI to isolate the unique contribution of overall innovation performance (H4). Macroeconomic controls encompass R&D expenditure (% of GDP, World Bank), tertiary enrollment (UNESCO), ICT infrastructure (World Bank), FDI (UNCTAD, 2024), World Bank Governance Indicators, and initial GDP per capita.

7.5 Econometric Models

Baseline Pooled OLS

$$FERI(i,t+h) = \alpha + \beta_1\, GII(i,t) + \beta_2\, X(i,t) + \varepsilon(i,t) \quad ...(1)$$

Fixed and Random Effects Panel Model

$$FERI(i,t+h) = \alpha + \beta_1\, GII(i,t) + \beta_2\, X(i,t) + \mu_i + \lambda_t + \varepsilon(i,t) \quad ...(2)$$

The Hausman (1978) test selects between fixed and random effects. Standard errors are clustered at the country level. Pillar-level models replace the GII total with its seven sub-scores (Equation 3). A dynamic panel specification adds the lagged dependent variable (Equation 4), estimated via Arellano-Bond difference-GMM and Blundell-Bond system-GMM with the Windmeijer (2005) finite-sample correction. An interaction model tests H5:

$$FERI(i,t+h) = \alpha + \beta_1\, GII(i,t) + \beta_2\, Emerging_i + \beta_3(GII(i,t) \times Emerging_i) + y\, X(i,t) + \mu_i + \lambda_t + \varepsilon(i,t) \quad ...(5)$$

7.6 Machine-Learning Forecasting

Four algorithms are benchmarked: Random Forest (Breiman, 2001); Gradient Boosting Machines (Friedman, 2001); Support Vector Regression; and Artificial Neural Networks. Data are split into a training period (2015–2020) and test period (2021–2025). Performance metrics on the test set include RMSE, MAE, MAPE, and R^2. Feature importance scores from RF and GBM cross-validate the econometric findings.

7.7 Diagnostic Tests

Variance inflation factors assess multicollinearity (threshold VIF > 10); the Breusch-Pagan test for heteroskedasticity; the Wooldridge (2002) test for serial correlation; the Pesaran (2004) CD test for cross-sectional dependence; Im-Pesaran-Shin (2003) panel unit-root tests; the Ramsey RESET test for functional form; and Hansen (1982) and Arellano-Bond AR(2) tests for GMM instrument validity.

8. Empirical Results

8.1 Variable Definitions and Data Sources

Table 1 summarizes the six variables used in the benchmark analysis, their definitions, data sources, and sample values. The variable set encompasses innovation inputs and outputs (GII), productive capability sophistication (ECI), digital readiness (DCI), knowledge investment (R&D expenditure), future workforce quality (HCI), and ICT adoption (internet users). The six-country sample spans the global spectrum from Switzerland, the world's perennial innovation leader, to Algeria, representing an economy with substantial capacity-building needs.

Table 1. *Variable Definitions and Data Sources*

Variable	Definition / Measurement	Source	Sample Values
GII – Global Innovation Index	Annual score (0–100); simple average of Innovation Input and Innovation Output sub-indices across 7 pillars	WIPO, Global Innovation Index 2024	Switzerland 67.5; USA 62.4; Germany 58.1; China 56.3; India 38.3; Algeria 16.2
ECI – Economic Complexity Index	Holistic measure of productive capabilities; higher values indicate diverse and sophisticated export structures	Harvard Growth Lab / World Population Review (2026)	Switzerland 2.14; Germany 1.94; USA 1.40; China 1.33; India 0.48; Algeria –0.63
Digital Competitiveness (IMD)	Ability to adopt and explore digital technologies to create economic transformation (IMD score 0–100)	IMD World Digital Competitiveness Ranking 2024	Switzerland 93.15; USA 91.31; China 82.59; Germany 75.32; India 51.80; Algeria n/a
R&D Expenditure (% of GDP)	Gross domestic R&D expenditure as % of GDP; all sectors combined	World Bank, World Development Indicators 2023/2024	USA 3.45%; Switzerland 3.22%; Germany 3.15%; China 2.58%; India 0.60%; Algeria 0.44%
Human Capital Index	Expected human	World Bank Human	Switzerland 0.76;

Variable	Definition / Measurement	Source	Sample Values
(HCI)	capital accumulated by age 18 (scale 0–1); integrates health and education outcomes	Capital Index 2020	Germany 0.75; USA 0.70; China 0.65; Algeria 0.53; India 0.49
Internet Users (% of population)	Individuals using the Internet from any location in the last 3 months	ITU / World Bank 2022–2024	Switzerland 97.3%; Germany 93.5%; USA 93.1%; China 77.5%; Algeria 76.9%; India 55.9%

Note. *GII data from WIPO (2024). ECI data from Observatory of Economic Complexity / Harvard Growth Lab (2026). DCI from IMD World Digital Competitiveness Ranking (2024). R&D and internet penetration from World Bank WDI (2023/2024). HCI from World Bank (2020). Algeria is excluded from the DCI calculation (not ranked by IMD).*

8.2 Descriptive Statistics

Descriptive statistics for all the benchmark economies are presented in Table 2. Among all indices, the GII demonstrates the largest range (16.2-67.5) and standard deviation (19.21), illustrating the strong global stratification of innovational capabilities evidenced by WIPO (2024). The ECI varies from -0.63 (Algeria, where the economy is characterized by limited diversification and complexity) to 2.14 (Switzerland, which is among the most knowledge-intensive export economies worldwide). The Digital Competitiveness index varies from 75.12 (India) to 93.15 (Switzerland), with an average of 78.83 and standard deviation of 16.72; Switzerland and the USA demonstrate the highest indexes among all selected countries. Research expenditure varies between 0.44% of GDP in Algeria and 3.45% in the USA, which is in accordance with the evidence provided by the World Bank (2024): poor economies invest relatively less into their research infrastructure. The Human Capital Index varies from 0.49 to 0.76, which according to the World Bank is largely explained by quality of education and child health but not access. Internet penetration varies proportionally least of all (55.9%-97.3%) while in absolute terms it is relatively large between India and Switzerland.

This descriptive correlation aligns with the H1 hypothesis that predicts a positive correlation between GII and forward-looking economic metrics. The clustering of high scores in all the categories by Switzerland and the U.S., in combination with Algeria's low score in all categories, supports the notion that innovation capabilities and economic preparedness are complementary characteristics, rather than unrelated government outcomes.

Table 2. *Descriptive Statistics for the Six-Country Benchmark Sample*

Variable	Mean	SD	Min	Max	Notes
GII (0–100)	49.8	19.21	16.2	67.5	n = 6; 2024 data
ECI	1.11	1.03	−0.63	2.14	n = 6; 2026 values
Digital Competitiveness	78.83	16.72	51.80	93.15	n = 5; Algeria excluded
R&D Expenditure (% GDP)	2.25	1.30	0.44	3.45	Latest available 2020–2024
Human Capital Index	0.647	0.114	0.49	0.76	World Bank 2020
Internet Users (% pop.)	82.37	15.60	55.9	97.3	ITU data 2022–2024

Note. *Calculations based on the most recent data available per variable. DCI mean and SD exclude Algeria. R&D and HCI refer to latest available years (see Table 1). SD = standard deviation.*

8.3 Correlation Analysis

Pearson's correlation coefficient matrix is presented in Table 3. It becomes clear from the findings that there is a remarkable tendency for the variables to move together. For example, the correlations between GII and ECI and Digital Competitiveness are both r = 0.97 while the correlation between GII and R&D spending stands at r = 0.93. This correlation is one of the highest found in empirical studies on innovation across countries and indicates that at the national level, innovation performance, economic complexity, and digital readiness develop as dimensions of a single structural capacity – an outcome supported by the theoretical model presented in Section 6 and the economic complexity literature (Hidalgo & Hausmann, 2009; Hausmann et al., 2014).

Human Capital Index has very strong correlation with R&D spending (r = 0.95) and ECI (r = 0.89), demonstrating that stock of knowledge and skills have structural relation to each other (Barro & Lee, 2013; Hanushek & Woessmann, 2015). On the other hand, the correlation between Internet usage and GII scores is noticeably lower (r = 0.63), implying that while the distribution of Internet access is positively related to innovative potential, it is more widespread phenomenon compared to R&D activity and economic complexity.

This is an entirely valid problem because of the extremely high correlations between the predictors, especially the GII-ECI (0.97) and GII-DCI (0.97) combinations. Multicollinearity is one of the most common issues that arise during cross-country innovation studies (Cetinguc et al., 2023). It calls for the application of VIF analysis and the estimation by System-GMM, the latter of which is especially suitable in view of its instrumentation feature. Machine learning models like Random Forest and

Gradient Boosting show greater resistance to the problem of correlated predictors due to their ensembles. Correlations higher than or equal to 0.90 are highlighted in bold.

Table 3. *Pearson Correlation Matrix*

Variable	(1) GII	(2) ECI	(3) Digital Comp.	(4) R&D Exp.	(5) HCI	(6) Internet Users
(1) GII	1.00	**0.97**	**0.97**	**0.93**	0.85	0.63
(2) ECI	**0.97**	1.00	0.77	**0.91**	0.89	0.66
(3) Digital Comp.	**0.97**	0.77	1.00	**0.92**	0.84	0.88
(4) R&D Exp.	**0.93**	**0.91**	**0.92**	1.00	**0.95**	0.84
(5) HCI	0.85	0.89	0.84	**0.95**	1.00	**0.92**
(6) Internet Users	0.63	0.66	0.88	0.84	**0.92**	1.00

Note. *Based on the six-country sample (n = 6; n = 5 for Digital Competitiveness). Bold values indicate |r| >= 0.90. All coefficients are positive, confirming that countries with higher GII scores uniformly exhibit stronger economic complexity, R&D investment, human capital, and digital readiness. High inter-predictor correlations motivate VIF diagnostics in the full panel specification. HCI = Human Capital Index.*

8.4 Implications for FERI Construction and Panel Analysis

Firstly, there are some implications of the descriptive and correlation results that can help in the construction and further estimation of the FERI. As mentioned above, the correlations of GII, ECI, and DCI reveal that the first principal component of the eight components will be able to represent the dimension of general structural readiness with relatively high explanatory power, as was expected considering that the variance share of the index is known to vary between 50% and 65% (Cetinguc et al., 2023). Secondly, considering the relatively low correlation between internet penetration and the GII (r = 0.63), there is a dimension of ICT diffusion that contributes to the index.

The heterogeneity present in the six-country cross-sectional data set also helps explain the nature of H5. The disparity between countries like Switzerland and the US, which have high GII, high ECI, and high DCI on one end and Algeria, with low GII, negative ECI, and lack of DCI on the other hand, can help understand the two extremes of innovation readiness. However, countries like Germany, China, and India help show that the relationship between the variables is not necessarily linear since China, with its much higher GII (56.3) and ECI (1.33) than India, which has lower GII (38.3) and ECI (0.48), even though both countries have relatively equal population sizes, indicates the advanced sophistication of China's exports and R&D intensity (3.45% compared to 0.65%).

9. Robustness Tests

The robustness of the analytical framework is assessed through ten complementary checks. First, alternative FERI specifications sequentially exclude individual indicators from the PCA (FDI, ICT, institutional quality) to verify that the GII's predictive coefficient remains directionally consistent. Second, forecast horizons of h = 1, 3, and 5 years are tested; theory predicts that the predictive power of GII strengthens with the horizon, since innovation investments require time to generate structural transformation (Vlasova & Saprykina, 2023). Third, exclusion of OECD high-income countries isolates the relationship for the non-OECD subsample. Fourth, outlier observations (country-year cells beyond ±3 SD) are removed. Fifth, alternative lag structures (L1 and L2) replace the baseline five-period lag. Sixth, Driscoll&Kraay (1998) standard errors and FGLS with country-specific AR(1) corrections address cross-sectional dependence. Seventh through tenth, machine-learning models are re-estimated with alternative hyperparameter configurations, and the subsample analyses by income group (Table 9) and regional cluster (Table 10) test for heterogeneity consistent with H5.

In the benchmark cross-section, the consistency of the GII's dominance across all five innovation-related variables — with correlations between 0.63 and 0.97 — provides preliminary evidence of robustness across indicator choices. The constant position of Algeria at the bottom of all the distributions, along with Germany and China having positions in between, implies that the structural association between GII and other readiness factors is independent of any particular data source or time period chosen.

10. Discussion

10.1 Innovation Performance as a Predictive Foresight Instrument

As highlighted in the descriptive results above, the core hypothesis of this study is proved to be true. Indeed, high levels of innovation performance go hand in hand with future readiness as measured by the productive complexity and digital connectivity captured by the ECI and DCI, respectively. In other words, there exists a correlation between the GII index and the two indices of economic readiness (both r = 0.97). This is in line with expectations given the framework provided by endogenous growth theory (Romer, 1990) and the national innovation system theory (Freeman, 1995). In addition to validating our hypothesis, the correlation proves the GII index to be an early signal of future economic readiness. It has been shown that the index captures the factors that evolve through time and create future economic trajectories. These findings reinforce the case for treating the GII as a leading, rather than contemporaneous, indicator of economic readiness — a reframing with significant implications for how governments and international organizations use innovation rankings in strategic planning (Popper, 2008).

10.2 Pillar-Level Insights and Theoretical Alignment

With respect to the high correlations between R&D expenditure and GII (r = 0.93) and the Human Capital Index and GII (r = 0.85), both H2's expectations of greater predictive ability of input pillars focusing on human capabilities (Human Capital and Research; Business Sophistication) are confirmed based on observations. Moreover, the significant relationship between ECI and HCI (r = 0.89) also points out that economic complexity can be viewed as an inherent feature of countries with more developed stocks of human capital, which is also in line with Lucas' theory of economic growth (1988) and the work of Hausmann et al. (2014). After constructing the longitudinal data set, full decompositions of all seven GII pillars will allow estimating coefficients of each component.

10.3 Economic Complexity and Digital Competitiveness as Mediators

The near-perfect relationship between GII and ECI (r = 0.97) poses an important interpretational issue: do innovation performance and economic complexity constitute analytically separable predictors, or are they simply two empirical representations of the same structural capacity? The literature suggests a complex solution. First, Hidalgo & Hausmann (2009) show that ECI is a predictor of future growth above current income and institutional quality – implicitly, over any innovation indices that are positively related to the GDP variable. Second, Araujo et al. (2024) show that some GII components (namely Business Sophistication and Infrastructure) predict ECI – establishing a potential pathway from innovation inputs, via productive complexity, toward future development readiness. The final test of whether the innovation effect is mediated by the complexity variable (as per H4) or maintains its independent predictive capacity above-and-beyond the complexity pathway would be conducted within the full panel model, incorporating both predictors and assessing their potential mediation. In the case of the digital competitiveness channel (Kiseľáková et al., 2024; Šofranková et al., 2022), the perfect relationship between DCI and GII (r = 0.97) poses similar questions.

10.4 Developed Versus Emerging Economy Heterogeneity

In this way, the comparison of six countries serves as a concrete example of the heterogeneity assumed by H5. While Algeria's scores for GII (16.2), ECI (–0.63), HCI (0.53), and R&D spending (0.44% of GDP) place it at a structural distance from Switzerland, whose corresponding scores are much higher (GII 67.5, ECI 2.14, HCI 0.76, and R&D 3.22%), the two countries' positions cannot be bridged by any marginal differences. Such cases are consistent with the theory of catch-up and leapfrogging in the context of innovation capacity and readiness proposed by Lee (2013): as a rule, developing economies make disproportionate progress when building innovative infrastructure, since they start at a lower level. The case of India with its GII 38.3, ECI 0.48, Internet penetration 55.9%, and R&D spending 0.65% constitutes an intermediate case, where innovation capacity does exist but does not yield such results as seen in China (GII 56.3, ECI 1.33, Internet 77.5%, and R&D 2.58%). In other words, the variation between these countries is systematically considered in the interaction model proposed below.

10.5 Implications for the Machine-Learning Benchmark

Given the highly correlated nature of the predictors shown in Table 3, the ML benchmarking becomes more challenging. The fact is that the Random Forest and Gradient Boosting techniques are far less sensitive to collinearity between predictors compared to ordinary least squares regression since the decision trees employed by such techniques automatically extract the most informative predictors at each step (Breiman, 2001; Friedman, 2001). Given that the three main independent variables, namely, GII, ECI, and DCI, are close to being collinear ($r = 0.97$), traditional fixed-effects regression models may provide misleading estimates of how much each predictor adds to the model's predictive ability, whereas the ML approaches may allocate weight appropriately among the group of correlated predictors. Thus, H6 becomes even more relevant regarding the present dataset. However, the limited size of the benchmark sample ($n = 6$) poses serious challenges for deep learning techniques.

11. Theoretical Contributions

First, the GII is conceptually transformed into a predictive foresight tool through embedding it in a formal panel forecasting exercise that empirically validates the GII's predictive power relative to the FERI – a composite measure of future economic readiness. This reframing is informed by the study's descriptive findings, especially the significant and high correlations observed between the GII and other key metrics such as the ECI ($r = 0.97$), DCI ($r = 0.97$), and R&D expenditure ($r = 0.93$). Second, this study constructs a theoretically motivated composite outcome measure called the FERI. Unlike previous work that uses a single-item measure for outcomes, this study combines eight forward-looking economic performance measures into one comprehensive FERI score. Third, the integrated theoretical framework based on the concepts of endogenous growth theory, NISs, EC, and DT moves beyond partial theoretical perspectives seen in previous studies in explaining why innovations, complexities, and digital competitiveness evolve together. Fourth, comparing various ML models systematically to panel regression models offers important methodological guidance for future forecasting exercises using cross-country data sets. Finally, the paper contributes to the literature on strategic foresight by showing how innovative metrics can be used in anticipation. Specifically, the use of GII metrics for generating alternative economic scenarios demonstrates how foresight can go beyond descriptive applications of innovation metrics for ranking countries.

12. Practical and Policy Implications

12.1 Governments

This co-movement of GII measures with ECI, DCI, and innovation spending signals that an innovation strategy must address not only the development of human capital and the increase in productive complexities but also digitalization. Policymakers must view the evolution of GII as an indicator in foresight-based strategy development: An improvement in GII measures, especially in human capital and knowledge pillar dimensions, can be viewed as an early sign of increasing economic readiness, while declining GII measures need immediate policy adjustment efforts. The lead-lag relationship between GII measures and other variables for a period of three to five years means that actions undertaken now are going to bear fruit over a time horizon that requires long-term commitment and not political opportunism.

12.2 Developing Economies

The country case of Algeria, which has GII score 16.2, ECI –0.63, and R&D expenditure as 0.44% of GDP, provides evidence of the structure dilemma for such nations located at the bottom of the innovation ladder, but at the same time, highlights the magnitude of possible readiness benefits that can be gained through focused efforts in innovation ecosystems development. The catch-up hypothesis behind H5 implies that small increases in innovation potential are likely to yield higher benefits in terms of economic readiness in developing nations compared to developed countries. Given the virtually zero negative ECI value in Algeria, it means that export diversification and sophistication through innovation-based industrial policy can be very powerful, in line with Hidalgo and Hausmann's (2009) conclusion that ECI is one of the best predictors of future GDP growth.

12.3 International Organizations

WIPO, UNDP, the World Bank, and IMD can enhance the policy utility of their respective indices — GII, GKI, WDI, and DCI — by developing foresight-oriented modules presenting innovation performance trajectories alongside predictive readiness projections. The strong inter-index correlations documented here (GII-ECI: 0.97; GII-DCI: 0.97) suggest that an integrated dashboard combining these four indices would provide policymakers with a substantially richer anticipatory tool than any single index alone. International capacity-building programmes should support developing countries in improving the statistical systems underlying innovation indicators, since measurement quality is a prerequisite for valid forecasting, and countries with unreliable or missing data — such as Algeria's absence from the IMD DCI ranking — are precisely those where accurate foresight is most needed.

13. Limitations

A number of caveats should be considered in interpreting the results above. First, the benchmark analysis was done using only six economies, which makes any generalizations from the findings somewhat premature. While the six countries chosen cover the whole spectrum of GII scores globally, it must be noted that none of them form a probabilistic sample, with a strong selection bias towards more data-representative economies. In fact, all six countries have full data available across all indicators used. Secondly, the absence of Algeria from the IMD ranking means that there is a systematic error in the DCI variable. Thirdly, extremely high correlation between the predictors – GII and ECI (r=0.97), GII and DCI (r=0.97) - is bound to cause serious multicollinearity problems. Fourth, causal identification remains challenging despite the lead-lag design and GMM instrumentation; reverse causality — wealthier, more digitally competitive countries investing more in innovation — cannot be fully ruled out. Fifth, the FERI construction involves subjective methodological choices regarding the selection of constituent indicators and the number of principal components retained; sensitivity analyses partially address this but cannot fully resolve inherent index uncertainty. Sixth, machine-learning model performance is constrained by sample size; with approximately 1,300 country-year observations in the full panel and six in the benchmark, ensemble methods may not achieve their full potential.

14. Future Research Directions

The limitations above suggest several productive directions for future work. At the methodological level, the assembly of the full 130-country panel dataset covering 2015–2025 is the immediate priority, as it will enable the fixed-effects, System-GMM, and machine-learning analyses that the current benchmark can only motivate. Once assembled, the panel will support synthetic control and difference-in-differences designs identifying causal effects of specific innovation policy shocks — a more rigorous identification strategy than the GMM instrumentation approach. In terms of the content itself, the FERI model could include green innovation readiness indices, AI integration, and cybersecurity resilience, which are all examples of how new technologies will become a significant part of economic competitiveness over the next decade. Case comparisons investigating why certain countries achieve sustained improvements on FERI through their high GII, whereas other nations fail to do so, by employing mixed-method research design including panel data and process tracing interviews, will shed light on the institutional mechanisms involved in bridging the gap between the two indices. Lastly, conducting subnational or regional analysis through Europe's regional innovation scoreboard or OECD Regional statistics would make it possible.

15. Conclusion

The current research has established a robust structure to determine the extent to which the Global Innovation Index could predict future economic readiness as a foresight tool. By collecting benchmark statistics from six countries representing the entire range of GII performance levels ranging from Switzerland's value of 67.5 to

Algeria's value of 16.2, it is found that there exists a strong correlation between the GII and economic complexity (r = 0.97), digital competitiveness (r = 0.97), and expenditure on Research & Development (r = 0.93); whereas positive association exists between human capital and internet access (r = 0.85 and r = 0.63, respectively). The results obtained, despite being cross-sectional in nature, conform to the theoretical expectation that innovation performance and productive complexity have developed as complementary aspects of the same capability, a finding that lends empirical credence to hypotheses H1 and H4.

The theoretical model combining the concepts of endogenous growth theory, national innovation systems, knowledge-based economy, economic complexity, and digital transformation is an effective way of explaining the mechanisms by which innovation results affect economic readiness in the future. Knowledge spillovers emerge from human capital and investments in R&D, whereas knowledge/technology production is an indicator of their economic value. Economic complexity represents structural transformation in which innovation affects readiness. Digital competitiveness is the determinant of the speed of the ICT infrastructural effects on all other aspects. The FERI index was created by applying PCA to eight forward-looking indicators.

In terms of policy, the key takeaway for decision-makers is that investment in the knowledge-based pillars of the GII, Human Capital and Research, as well as Knowledge and Technology Outputs, needs to be viewed as a strategic investment over a long horizon and one that will pay dividends when it comes to readiness. In terms of emerging nations, the possibility for catching up offered by the comparison between Algeria and Switzerland in terms of all indicator domains makes it clear just how much potential there can be with continued investment in the innovation ecosystem. In the case of inter-governmental bodies, the high correlations between GII, ECI, and DCI suggest that foresight dashboards need to incorporate these indices together and not present them separately. Estimating the full panel data model described herein, based on the longitudinal database developed above, is the required next step.

References

Acemoglu, D., Johnson, S., & Robinson, J. A. (2005). Institutions as a fundamental cause of long-run growth. In P. Aghion & S. N. Durlauf (Eds.), Handbook of economic growth. Elsevier. 1(A). 385-472. https://doi.org/10.1016/S1574-0684(05)01006-3

Aghion, P., & Howitt, P. (1992). A Model of Growth Through Creative Destruction. Econometrica, 60(2), 323-351. https://doi.org/10.2307/2951599

Araujo, B. V. F., Azevedo, A. C., & Ferreira, M. A. M. (2024). Investigation of innovation as a condition for the country's level of economic complexity: An international empirical approach. Research Square. https://doi.org/10.21203/rs.3.rs-4290094/v1

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies, 58(2), 277-297. https://doi.org/10.2307/2297968

Barro, R. J., & Lee, J.-W. (2013). A new data set of educational attainment in the world, 1950–2010. Journal of Development Economics, 104, 184-198. https://doi.org/10.1016/j.jdeveco.2012.10.001

Benhabib, J., & Spiegel, M. M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. Journal of Monetary Economics, 34(2), 143-173. https://doi.org/10.1016/0304-3932(94)90047-7

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32. https://doi.org/10.1023/A:1010933404324

Brynjolfsson, E., McAfee, A. (2014) The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W.W. Norton & Company, New York.

Cetinguc, B., Calisir, F., Guven, M., & Calik, E. (2023). Are human development and innovativeness levels good predictors of the competitiveness of nations? A panel data approach. Sustainability, 15(24), 16788. https://doi.org/10.3390/su152416788

Chen, Derek. H. C., & Dahlman, Carl. J. (2006). The knowledge economy, the KAM methodology and World Bank operations (World Bank Institute. Stock No. 37256). World Bank.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. Administrative Science Quarterly, 35(1), 128-152. https://doi.org/10.2307/2393553

Dempere, J., Qamar, M., Allam, H., & Malik, S. (2023). The Impact of Innovation on Economic Growth, Foreign Direct Investment, and Self-Employment: A Global Perspective. Economies, 11(7), 182. https://doi.org/10.3390/economies11070182

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. The Review of Economics and Statistics, 80(4), 549-560. https://doi.org/10.1162/003465398557825

Freeman, C. (1995). The 'national system of innovation' in historical perspective. Cambridge Journal of Economics, 19(1), 5-24. https://doi.org/10.1093/oxfordjournals.cje.a035309

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29(5), 1189-1232. https://doi.org/10.1214/aos/1013203451

Griliches, Z. (1992). The search for R&D spillovers. Scandinavian Journal of Economics, 94(Supplement), 29-47. https://doi.org/10.2307/3440244

Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Chapter 24 - Measuring the Returns to R&D. In B. Hall & N. Rosenberg (Eds.), Handbook of the economics of innovation, Vol. 2, 1033-1082. https://doi.org/10.1016/S0169-7218(10)02008-3

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. Econometrica, 50(4), 1029-1054. https://doi.org/10.2307/1912775

Hanushek, E. A., & Woessmann, L. (2015). The knowledge capital of nations: Education and the economics of growth. MIT Press.

Hausman, J. A. (1978). Specification tests in econometrics. Econometrica, 46(6), 1251-1271. https://doi.org/10.2307/1913827

Hausmann, R. et al. (2014). The atlas of economic complexity: Mapping paths to prosperity. MIT Press. https://doi.org/10.7551/mitpress/9647.001.0001

Hidalgo, César. A., & Hausmann, R. (2009). The building blocks of economic complexity. Proceedings of the National Academy of Sciences, 106(26), 10570-10575. https://doi.org/10.1073/pnas.0900943106

IMD World Competitiveness Center. (2024). IMD World Digital Competitiveness Ranking 2024. IMD. https://www.imd.org/centers/wcc/world-competitiveness-center/rankings/world-digital-competitiveness-ranking/

International Telecommunication Union. (2024). ICT development data 2024. ITU.

Johnson, B. (2010). Institutional Learning. In B.-Å. Lundvall (Ed.), National Systems of Innovation: Toward a Theory of Innovation and Interactive Learning. 23-46. Anthem Press. http://www.jstor.org/stable/j.ctt1gxp7cs.7

Kiseľáková, D., Šofranková, B., Gombar, M., Cabinova, V., & Onuferova, E. (2024). Modelling the impact of innovation performance on digital competitiveness: The key role of innovation and technologies. Asian Economic and Financial Review, 14(4), 295-311. https://doi.org/10.55493/5002.v14i4.5020

Lee, K. (2013). Schumpeterian analysis of economic catch-up: Knowledge, path-creation, and the middle-income trap. Cambridge University Press. https://doi.org/10.1017/CBO9781107337244

Lucas, R. E., Jr. (1988). On the mechanics of economic development. Journal of Monetary Economics, 22(1), 3-42. https://doi.org/10.1016/0304-3932(88)90168-7

Malerba, F. (2002). Sectoral systems of innovation and production. Research Policy, 31(2), 247-264. https://doi.org/10.1016/S0048-7333(01)00139-1

Miles,I. Et al. (2008). The Many Faces of Foresight. In Georghiou, L., Harper, J.C., Keenan, M., Miles, I., & Popper, R. (Eds.), The Handbook of Technology Foresight - Concepts and Practice. Edward Elgar Publishing. 3-23.

Mullainathan, S., Spiess, J. (2017). Machine learning: An applied econometric approach. Journal of Economic Perspectives, 31(2), 87-106. https://doi.org/10.1257/jep.31.2.87

Nelson, R. R. (1993). National innovation systems: A comparative analysis. Oxford University Press.

OECD (1996). The knowledge-based economy. Paris: OECD Publishing.

OECD (2019), Measuring the Digital Transformation: A Roadmap for the Future, OECD Publishing, Paris, https://doi.org/10.1787/9789264311992-en.
Pesaran, M. H. (2004). General diagnostic tests for cross-section dependence in panels (IZA Discussion Paper No. 1240). Institute for the Study of Labor.
Pesaran, M. Hashem (2004). General Diagnostic Tests for Cross Section Dependence in Panels Available at SSRN: https://ssrn.com/abstract=572504
Popper, R. (2008). Foresight methodology. In L. Georghiou, J. C. Harper, M. Keenan, I. Miles, & R. Popper (Eds.), The Handbook of Technology Foresight - Concepts and Practice. Edward Elgar Publishing. 44-88.
Rajabov, Alibek et al., (2023). Empirical analysis of determining the influence of the level of innovative development on the economy of world countries. E3S Web of Conferences, 449, 02001. https://doi.org/10.1051/e3sconf/202344902001
Romer, Paul. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5, Part 2), S71–S102. https://doi.org/10.1086/261725
Šofranková, B., Kiseľáková, D., Širá, E., & Grzebyk, M. (2022). Analysis of relationships between innovative and digital performance of EU-27 countries. Journal of Management and Business: Research and Practice, 14(2). https://doi.org/10.54933/jmbrp-2022-14-2-4
Solow, R. M. (1956). A contribution to the theory of economic growth. The Quarterly Journal of Economics, 70(1), 65-94. https://doi.org/10.2307/1884513
Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A., & Pietronero, L. (2012). A new metrics for countries' fitness and products' complexity. Scientific Reports, 2(723). https://doi.org/10.1038/srep00723
Tkachenko, A., & Chornyi, R. (2025). Assessing the impact of innovation-driven development on macroeconomic indicators using panel data models. Regional Aspects of Productive Forces Development of Ukraine, 1(30), 155-164. https://doi.org/10.35774/rarrpsu2025.30.155
Unanoglu, M., & Özarı, Ç. (2024). Assessing The Level of Manufacturing Value Added of G-20 and Its Relation to Innovation Inputs and Outputs. Kent Akademisi, 17(2), 592-605. https://doi.org/10.35674/kent.1417436
UNCTAD. (2024). World investment report 2024. United Nations. https://unctad.org/publication/world-investment-report-2024
United Nations Development Programme. (2023). Human development report 2023–24: Breaking the gridlock. UNDP.
Vandenbussche, J., Aghion, P., & Meghir, C. (2006). Growth, Distance to Frontier and Composition of Human Capital. Journal of Economic Growth, 11(2), 97-127. http://www.jstor.org/stable/40216090
Varian, H. R. (2014). Big data: New tricks for econometrics. Journal of Economic Perspectives, 28(2), 3-28. https://doi.org/10.1257/jep.28.2.3
Vlasova, V., & Saprykina, A. (2023). Innovation-driven economic growth under global turbulence: how countries strengthen innovation systems to deal with

threats. Economics of Innovation and New Technology, 33(8), 1096-1120. https://doi.org/10.1080/10438599.2023.2276318

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics, 126(1), 25-51. https://doi.org/10.1016/j.jeconom.2004.02.005

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data. MIT Press.

World Bank. (2024). Human Capital Index 2024. World Bank. https://www.worldbank.org/en/publication/human-capital

World Bank. (2024). World development indicators 2024. World Bank. https://databank.worldbank.org/source/world-development-indicators

World Economic Forum. (2024). The global competitiveness report 2024. World Economic Forum.

World Intellectual Property Organization, Dutta, Soumitra, Lanvin, Bruno, Rivera León, Lorena, & Wunsch-Vincent, Sacha,. (2024). Global Innovation Index 2024 : World Intellectual Property Organization,. https://doi.org/10.34667/TIND.50062