"Cross-sectional mediation evidence with panel robustness checks of economic complexity, logistics performance, and country innovation, 2020–2024"

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CROSS-SECTIONAL MEDIATION EVIDENCE WITH PANEL ROBUSTNESS CHECKS OF ECONOMIC COMPLEXITY, LOGISTICS PERFORMANCE, AND COUNTRY INNOVATION, 2020–2024

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Abstract

This study examines whether logistics performance mediates the relationship between economic complexity and national innovation outcomes. The sample comprises the top-20 economies of the Global Innovation Index (2025) and Ukraine, observed over 2020–2024. The mediation model is estimated on the 2024 cross-section (n = 21) using OLS and the Baron–Kenny procedure. Cross-sectional point estimates indicate an indirect effect via the Logistics Performance Index of 7.585 GII points, 46.3% of the total effect (c = 16.366, $p < 0.001$), while the software–expenditure channel fails the Baron–Kenny conditions. The pooled panel corroborates the channel: the indirect effect equals 6.551 points (52.0% of the total effect), with the LPI–GII path highly significant ($p < 0.001$). Sensitivity analysis shows that the mediation is identified primarily by the contrast between the innovation frontier and Ukraine: excluding Ukraine, the ECI–LPI path loses significance while the LPI–GII path remains robust, consistent with saturation of the logistics channel within the frontier, where LPI varies only between 3.6 and 4.3. The bootstrap confidence interval for the indirect effect includes zero at n = 21, so the mediation findings are suggestive rather than confirmatory. Fixed-effects estimation shows that the ECI–GII relationship is predominantly structural (within-R^2 = 0.056), while LPI retains within-country significance (β = 3.60, p = 0.042). An illustrative arithmetic scenario translates Ukraine's LPI gap to the sample median into approximately 16 GII points. Findings position logistics infrastructure as a first-order margin for catching-up economies seeking to convert productive complexity into innovation capacity.

Keywords economic complexity, innovation performance, global value chains, logistics performance, mediation analysis, panel regression, supply chain digitalization

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INTRODUCTION

The national innovation capacity has emerged as a primary determinant of long-run competitive advantage and income convergence. The Global Innovation Index (GII) has become the dominant composite benchmark for tracking countries' performance across the full innovation value chain, and its trajectories reveal persistent and widening gaps between economies at different stages of development (Cornell University et al., 2024; WTO, 2025). Understanding the structural drivers of these gaps has moved to the center of both academic research and policy discourse.

Two constructs have attracted particular scholarly attention in this context. Economic complexity, operationalized through the Economic

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Complexity Index (ECI) developed by Hidalgo and Hausmann (2009), captures the diversity and sophistication of a country's productive knowledge base as reflected in its export structure. A growing body of evidence confirms that ECI predicts income levels, growth rates, and innovation outcomes with considerable accuracy across income groups (Hartmann et al., 2017; Balland et al., 2022; Solingen, 2025). Concurrently, logistics infrastructure, measured through the World Bank's Logistics Performance Index (LPI), has been identified as a critical enabler of knowledge diffusion, market integration, and R&D location decisions by multinational firms (Ekici et al., 2019; Negi, 2021; Gereffi et al., 2025; Ghobakhloo et al., 2025; Samuels, 2025). However, the role of logistics efficiency as a mediating channel in the ECI–GII system has received virtually no direct empirical examination. The digitalization of supply chains has further complicated this picture. In contrast, Wang and Prajogo (2024) and Wu et al. (2025) document that digital capital expenditure can amplify supply chain performance; they also find that returns are highly context-specific and depend on institutional integration depth, a pattern that may explain why software expenditure ratios are imperfect national-level predictors of innovation capacity.

1. LITERATURE REVIEW

The theoretical grounding for the Economic Complexity Index (ECI)–innovation nexus derives from the capability-based theory of economic development. Hidalgo and Hausmann (2009) demonstrated that ECI, constructed as the leading eigenvector of a bipartite country-product matrix, encodes the diversity and exclusivity of productive capabilities embedded in a country's export structure. This spectral estimator outperforms income-based measures in predicting long-run growth precisely because it captures the latent knowledge stock underlying production rather than its immediate monetary valuation. Hartmann et al. (2017) extended this framework to show that countries with higher ECI exhibit systematically lower income inequality, suggesting that complexity shapes aggregate output and also the distributional consequences of structural change. Balland et al. (2022) further articulated a "new paradigm of economic complexity" in which relatedness, diversification, and complexity interact to determine regional and national development trajectories. Hidalgo (2023) formalized the policy implications of this paradigm through a 4Ws framework, arguing that structural transformation of productive capacity constitutes the operative policy mechanism for sustained innovation gains. Krammer (2009), examining Eastern European transition economies, confirmed that ECI-proxied structural factors predict national innovation performance, but that payoffs accumulate over long lags, consistent with the slow-moving nature of capability accumulation documented in the broader literature.

The relationship between logistics infrastructure quality and economic performance has been extensively documented at the aggregate level. Ekici et al. (2019) demonstrated, using Global Competitiveness Index pillar data, that improvements in logistics-related infrastructure dimensions produce statistically significant gains in national competitiveness across OECD and non-OECD samples. Negi (2021) developed a supply chain efficiency framework linking logistics capability to business performance, identifying customs efficiency, infrastructure quality, and tracking capability as the primary operational levers through which logistics translates into productivity gains. Polat et al. (2023), applying data envelopment analysis across OECD members, confirmed that logistics competitiveness and innovation capability are jointly determined, a finding that directly motivates the mediation hypothesis tested in the present paper.

Çelebi (2021) provided the closest existing evidence for our mediation model, showing that LPI has a significant positive effect on GDP through the mediating roles of FDI and patents, though without establishing the ECI–LPI–GII chain specifically. Sharawi et al. (2025), analyzing 105 countries over 2007–2023, confirmed that the sub-components of LPI, particularly timeliness and tracking, are the dominant drivers of overall logistics performance, while customs efficiency shows the highest cross-country variation, suggesting heterogeneous reform potential. The mechanisms through which LPI mediates innovation are coherent and multi-channeled: efficient logistics reduces the coordination costs of complex produc-

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tion networks, lowers R&D location barriers for multinational firms, and facilitates knowledge spillovers by shortening the physical and temporal distance between knowledge-generating and knowledge-using actors. Kayar and Avsar (2025), integrating GII and LPI data across G7 and BRICS economies, confirmed that innovation dynamics translate into logistics competitiveness through mutually reinforcing structural channels.

The digital transformation of supply chains has been widely posited as a primary amplifier of productive complexity in the knowledge economy. Wang and Prajogo (2024) demonstrated, using firm-level data, that supply chain digitalization positively affects performance through mediated pathways of supply chain agility and innovation capability. However, Wu et al. (2025) identified a "digitalization paradox": returns to digital investment are contingent on the specificity of existing resources and the depth of operational integration, implying that aggregate software expenditure ratios may be poor guides to the actual digital channel of innovation capacity. At the country level, raw software expenditure as a share of GDP conflates investment volumes with investment quality and is denominated downward in high-complexity economies with larger GDPs.

Several studies have examined the temporal dynamics of the complexity–innovation relationship more directly. Ashraf et al. (2023), using generalized panel quantile regression across economies, established that global value chain integration and ECI jointly determine innovation capacity, with the relationship exhibiting significant non-linearity across the complexity distribution. Şanlı et al. (2024), analyzing countries by income sub-group, confirmed that the drivers of ECI differ systematically by development level, underscoring the importance of income-group heterogeneity in any panel specification. Balland et al. (2022) and Hidalgo (2023) emphasize that global value chain centrality patterns are deeply embedded and change slowly, implying that innovation payoffs from structural complexity accumulate over multi-year lags. Finally, Ukraine's position within this analytical framework merits specific attention. Ukraine's pre-war ECI of 0.590 in 2020 reflected a moderately complex productive structure: Above the lower-middle-income average but below the high-income frontier. The war-induced economic disruption drove ECI to 0.359 by 2024, a 39.2% decline that is unprecedented among non-conflict transition economies (Growth Lab, Harvard Kennedy School, 2024).

The theoretical background of the research rests on three complementary arguments. First, complex production systems require precise coordination of material flows among specialized suppliers, and logistics inefficiency directly increases the transaction costs of such coordination (Negi, 2021). Second, logistics infrastructure is a prerequisite for participation in global value chains, through which economies access foreign technology and knowledge (Ashraf et al., 2023). Third, the quality of customs procedures and supply chain transparency conditions multinational firms' location decisions for R&D facilities (Ekici et al., 2019; Çelebi, 2021).

Against this background, this paper addresses the core scientific problem of whether, and to what extent, logistics efficiency transmits productive complexity into national innovation outcomes, and where in the development distribution this transmission operates. Thus, four hypotheses are formulated.

H1: *Economic complexity is positively associated with national innovation performance (total effect).*

H2: *Logistics performance mediates the ECI–GII relationship.*

H3: *Software expenditure mediates the ECI–GII relationship.*

H4: *Logistics performance moderates (amplifies) the ECI–GII relationship.*

2. METHOD

This study estimates a mediation model of the Economic Complexity Index (ECI) and Global Innovation Index (GII) relationship for 21 economies observed over 2020–2024, with logistics performance (LPI) and software expenditure (SW_{exp}) as candidate mediators. The mediation model is

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estimated on the 2024 cross-section; the panel dimension of the data serves to verify that the association is not an artefact of a single-year cross-section, to decompose it into between-country and within-country components, and to corroborate the mediation in a pooled panel estimation. The 2020–2024 window captures post-COVID-19 structural adjustment dynamics and encompasses the LPI publication wave transition from the 2018 to the 2023 values.

The sample comprises the top-20 economies of the Global Innovation Index 2025 and Ukraine (21 economies; 105 country-year observations; the full list is provided in Appendix A). The inclusion criterion was complete availability of all six variables for each year from 2020 to 2024; no top-20 economy violated this criterion. The design is intentional. The frontier sample maximizes variation in ECI and GII at the innovation frontier, where the mediation mechanism is expected to operate, while Ukraine is included as the focal policy case and is explicitly treated as an out-of-group observation, whose influence on the estimates is examined directly in the sensitivity analysis. Consequently, the findings characterize transmission at the innovation frontier and its contrast with a catching-up economy, and cannot be generalized to the full distribution of countries.

Six variables are employed. The dependent variable is the Global Innovation Index (GII), published annually by WIPO, which aggregates 81 indicators across seven pillars spanning innovation inputs and outputs (range: 29.5–67.5; mean = 55.41 in 2024) (WIPO, 2020, 2021, 2022, 2023, 2024; Global Innovation Index, 2024, n.d.). The primary independent variable is the Economic Complexity Index (ECI), sourced from Harvard Dataverse (HS92 classification) (Growth Lab, Harvard Kennedy School, 2024), which measures the diversity and sophistication of a country's export basket (range: 0.359–1.729; mean = 1.169 in 2024). Two candidate mediators are specified. Software expenditure is a share of GDP, a proxy for digital capital investment (range: 0.12%–1.26%; mean = 0.512%) (World Intellectual Property Organization (WIPO), n.d.). The Logistics Performance Index of the World Bank (World Intellectual Property; Logistics Performance; World Bank, n.d.) aggregates six sub-dimensions (customs efficiency, infrastructure quality, ease of arranging shipments, logistics service quality, tracking and tracing, and timeliness) on a scale of 1 to 5 (range: 2.70–4.30; mean = 3.852). Two control variables are included: the share of high-technology exports in manufactured exports (HT_{exp}) (World Bank Open, n.d.) and the annual GDP growth rate (GDP_{gr}) (World Economics, n.d.; Trading Economics, n.d.), capturing structural export orientation and macroeconomic cycle effects, respectively.

Because LPI is published biennially, the 2018 wave is assigned to the 2020–2021 observations and the 2023 wave to the 2022–2024 observations. This carry-forward assignment introduces measurement error of the interval-censoring type: within-wave variation in true logistics performance is suppressed, which attenuates estimated LPI coefficients toward zero in the within-country dimension, rendering the fixed-effects estimate of the LPI effect conservative and concentrating identifying variation at the 2021–2022 wave transition. The 2024 cross-sectional estimates rely solely on the 2023 wave and are unaffected by the carry-forward. This limitation is shared by all country-level studies employing LPI.

The estimation strategy proceeds in three stages. The first stage establishes the cross-sectional evidence. Table 2 shows descriptive statistics (Table 1) and Pearson correlations on the 2024 cross-section and the full panel. Table 3 shows OLS specifications M1–M4 on the 2024 cross-section, where M1 regresses GII on ECI, M2 adds SWexp, M3 adds LPI (the preferred specification by AIC), and M4 adds a mean-centered interaction ECIc*LPIc to test moderation. Table 4 shows the Baron–Kenny (1986) four-step mediation decomposition complemented by a nonparametric bootstrap mediation analysis (1,000 simulations, percentile confidence intervals, seed = 42; Table 5, Panel E). Mean-centering of ECI and LPI in M4 reduces the interaction VIF from 25.3 to 1.03.

The second stage verifies the statistical assumptions: multicollinearity via VIF (threshold 5; Table 5, Panel A), residual normality via the Shapiro–Wilk test (Panel B), homoscedasticity via the Breusch–Pagan test (Table 7) with HC3 heteroscedasticity-consistent standard errors as an additional check (Table 6, Panel B), and effect-size de-

Table 1. Descriptive statistics (cross-section 2024, n = 21)

Variables	Min	Max	Mean	SD	Source	Role in model
GII	29.5	67.5	55.41	7.84	WIPO	Dependent variable (Y)
ECI	0.359	1.729	1.169	0.320	Harvard Dataverse (HS92)	Independent variable (X)
LPI	2.70	4.30	3.852	0.336	World Bank	Mediator M2/moderator
SW_{exp}, %	0.12	1.26	0.512	0.242	IMF WEO	Mediator M1
HT_{exp}, %	6.37	75.57	27.80	16.85	World Bank WDI	Control variable
GDP_{gr} %	–1.4	5.1	0.93	1.59	IMF WEO	Control variable

composition via standardized coefficients, partial R^2, and incremental ΔR^2 (Table 6, Panel A).

The third stage exploits the panel and probes identification. We assess panel structure via the Breusch–Pagan LM and Hausman tests (Table 5, Panel C); the fixed-effects within estimator with Driscoll–Kraay standard errors isolates the within-country component (Panel D). A pooled panel mediation estimation on all 105 observations, with year fixed effects and country-clustered standard errors, re-estimates the total effect and both mediation paths on the full panel (Table 8). Sensitivity analyses include excluding two structural outliers in high-technology exports, Ireland and Hong Kong (Panel F). The exclusion of Ukraine as the out-of-group observation, together with a leave-one-out influence analysis over all 21 economies (Panel H); and an illustrative arithmetic scenario for Ukraine computed as b2*ΔLPI, where ΔLPI is the gap between Ukraine's LPI of 2.70 and the sample median of 3.87 (Panel G). Calculations are performed in R 4.3.3 (plm, lmtest, sandwich, mediation, car).

3. RESULTS

Table 2 reports the bivariate Pearson correlations for the 2024 cross-section (n = 21) and the full panel (n = 105). The strongest association in the matrix is r(GII, LPI) = 0.765 ($p < 0.001$, $r^2 = 0.585$). Logistics performance alone accounts for 58.5% of GII variance before introducing any other variable. This single coefficient constitutes preliminary evidence for the central hypothesis of the study. The ECI–GII correlation $r = 0.668$ ($p < 0.001$, $r^2 = 0.446$) is the second-strongest, confirming the relevance of economic complexity as a predictor. Crucially, both GII–SW_{exp} (r = 0.241, n.s.) and ECI–SW_{exp} (r = –0.179, n.s.) are statistically non-significant, directing attention toward the indirect rather than direct role of digital expenditure. This result foreshadows the mediation findings.

The full-panel correlation (n = 105) is computed as a pooled Pearson correlation on all country-year observations, treating the panel as a single cross-section of 105 data points (df = 103). The resulting t-statistic of 7.76 ($p < 0.001$) therefore reflects between- and within-country covariation jointly, rather than a within-FE estimate. This pooled r = 0.607 serves solely to confirm that the ECI–GII association is not an artefact of a single year's cross-section; the fixed-effects decomposition reported in the panel specification below separates these two sources of variation.

Table 3 reports the OLS estimates for specifications M1 through M4. The baseline model M1 yields β(ECI) = 16.366 (SE = 4.18, p < 0.001), R2 = 0.417 (AIC = 138.66). Adding SWexp in M2 raises R2 to 0.581, but the positive β(SWexp) = 12.072 (p < 0.05) captures a conditional association rather than an autonomous direct effect, as the non-significant bivariate correlation suggests.

The inclusion of LPI in M3 constitutes the most substantive improvement in fit: R^2 rises to 0.740, with β(LPI) = 11.471 ($p < 0.01$), while the coefficient on ECI falls to 11.005 ($p < 0.01$), a reduction of approximately 33% relative to M1, providing preliminary evidence consistent with mediation. β(SW_{exp}) declines to 8.588 and becomes only marginally significant, suggesting that part of its apparent effect in M2 captured the omitted LPI.

The inclusion of LPI in M3 constitutes the most substantive improvement in fit: R^2 rises from 0.581 to 0.740, with β(LPI) = 11.471 ($p < 0.01$). The coefficient on ECI falls to 11.005 ($p < 0.01$), a reduction of approximately 33% relative to M1, providing preliminary evidence of mediation. Simultaneously, β(SW_{exp}) declines to 8.588 and becomes only mar-

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Table 2. Pearson correlation matrix (n = 21, cross-section 2024; n = 105 for full-panel row)

Pair	r	r²	t-stat	p	n	Strength	Interpretation
ECI–GII (n = 21, 2024)	0.668	0.446	3.91	<0.001	21	Strong	ECI explains 44.6% of GII variance
ECI–GII (full panel, n = 105)	0.607	0.369	7.76	<0.001	105	Strong	Confirmed beyond single-year cross-section
GII–LPI	0.765	0.585	5.18	<0.001	21	Strong	Strongest pair in matrix: LPI explains 58.5% of GII
ECI–LPI	0.543	0.295	2.82	<0.05	21	Moderate	More complex economies have better logistics
GII–SW_{exp}	0.241	0.058	1.08	n.s.	21	Weak	Direct linear effect absent → indirect channel
ECI–SW_{exp}	–0.179	0.032	–0.79	n.s.	21	Weak	No significant association

Table 3. OLS regression results: Models M1–M4 (cross-section 2024, n = 21)

Parameter	M1	M2	M3	M4
Intercept	36.278	28.187	–6.041	51.693
β_1 (ECI/ECI_c)	16.366, *p<0.001*	18.001, *p < 0.001*	11.005, *p < 0.01*	10.198, *p < 0.05*
β_2 (SW_{exp})	–	12.072, *p < 0.05*	8.588, *p > 0.10*	8.009, *p > 0.10*
β_3 (LPI/LPI_c)	–	–	11.471, *p < 0.01*	8.847, *p > 0.10*
β_4 (ECI_c*LPI_c)	–	–	–	–6.895 n.s.
R^2	0.446	0.581	0.740	0.755
adj. R^2	0.417	0.534	0.694	0.693
AIC	138.66	134.82	126.83	127.57
N	21	21	21	21

ginally significant, suggesting that a portion of the apparent effect of software expenditure in M2 was in fact capturing the omitted LPI. The AIC improvement (126.83 versus 138.66) corroborates M3 as the preferred specification. In M4, the centered interaction β4 = –6.895 (p = 0.335) is not significant (VIF after centering 1.03; AIC = 127.57), so the moderation hypothesis H4 is rejected and M3 is retained. The large intercept in M4 reflects predictor centering and carries no substantive interpretation.

The fixed-effects (FE) panel specification on the full sample (n*T = 105) yields a strikingly different within-country picture. The Breusch–Pagan LM test (LM = 128.9, p < 0.001) decisively rejects pooled OLS. The Hausman test (χ^2 = 20.0, p = 0.001) favors FE. Within the FE estimator, β(ECIc) = –0.54 (n.s.), β(LPIc) = 3.60 (p = 0.042), and within-R2 = 0.056. The low within-R2 is a substantive finding: year-to-year changes in ECI within a country account for only 5.6% of year-to-year changes in GII, establishing that the cross-sectional ECI-GII relationship is predominantly a between-country structural phenomenon (H1 supported in the structural dimension).

Table 4 presents the Baron–Kenny decomposition of the total effect c = 16.366 (p < 0.001). For the LPI channel, a_2 = 0.569 (p = 0.011) and b_2 = 13.340 (p = 0.002); the indirect effect a2*b2 = 7.585 GII points, 46.3% of the total effect, and the direct effect c′ = 11.005 (p = 0.010) remains significant, a pattern consistent with partial mediation (H2 supported in point estimates). The total indirect effect (36.4%) is smaller than the LPI-alone share because the SW_{exp} channel contributes a negative component (–1.635, –10.0%); since a1 is non-significant, the 46.3% figure is the substantively meaningful estimate of the logistics channel. The SW_{exp} channel fails the second Baron–Kenny condition (a1 = –0.135, p = 0.437), so H3 is rejected. Thus, more complex economies do not spend a larger share of GDP on software, plausibly reflecting the GDP denominator effect or the substitution of targeted digital solutions for raw IT spending. In contrast, b1 = 12.072 (p = 0.027) is significant; SW_{exp} operates as a conditional direct predictor rather than a mediated channel of complexity.

Robustness is assessed through bootstrap mediation, assumption diagnostics, and sensitivity analyses, reported in Table 5. The bootstrap (Panel E) yields ACME = 7.585 with 95% CI [–0.581; 15.499], p = 0.124: the indirect effect does not attain conventional significance at n = 21, an outcome consistent with the established power limitations of small-sample mediation analysis. The individual paths remain significant (a2: p = 0.011; b2: p = 0.002), the total effect is confirmed (p = 0.008),

Table 4. Baron–Kenny mediation analysis (cross-section 2024, n = 21)

Step	Path	B	SE	t	p	Result
1 (c)	ECI–GII (total effect)	16.366	4.18	3.91	<0.001	Confirmed
2a (a_1)	ECI–SW_{exp}	−0.135	0.171	−0.79	0.437	Not confirmed (n.s.)
3a (b_1)	SW_{ex}p–GII/ECI	12.072	5.02	2.40	0.027	Confirmed in isolation
2b (a_2)	ECI–LPI	0.569	0.202	2.82	0.011	Confirmed
3b (b_2)	LPI–GII/ECI	13.340	3.73	3.57	0.002	Confirmed
4 (c′)	ECI–GII/SWexp+LPI	11.005	3.77	2.92	0.010	Partial mediation
–	Indirect via SW_{exp} (a_1*b_1)	–1.635	–	–	–10.0%	SWexp: not a mediator (a_1 n.s.)
–	Indirect via LPI (a_2*b_2)	7.585	–	–	46.3%	Principal candidate channel
–	Total indirect	5.950	–	–	36.4%	–
–	Direct effect (c′)	11.005	–	–	67.2%	ECI retains significance

and the direct effect is significant (ADE = 8.781, p = 0.012). The proportion mediated (0.463) matches the Baron–Kenny point estimate. The bootstrap results are therefore best interpreted as suggestive rather than confirmatory evidence of partial mediation. All VIF values are below 1.55 (Panel A); the Shapiro–Wilk test confirms residual normality (W = 0.965, p = 0.622; Panel B); panel-structure tests support FE with Driscoll–Kraay standard errors (Panel C), under which β(LPIc) = 3.60 (p = 0.042) remains significant (Panel D). Excluding the two high-technology-export outliers, Ireland and Hong Kong, leaves the result intact (β(LPI) = 11.20, p = 0.008, R2 = 0.731; Panel F).

The exclusion of Ukraine (Panel H) is far more consequential. Without Ukraine (n = 20), β(LPI) in M3 falls to 7.611 and loses significance (p = 0.127), R2 falls from 0.740 to 0.442, the total effect falls to 8.465 (p = 0.058), and, critically, the first mediation link collapses, a2 = 0.137 (p = 0.467) versus 0.569 (p = 0.011) in the full sample, while b2 declines to 8.829 (p = 0.099). A leave-one-out influence analysis over all 21 economies confirms that no other single exclusion materially alters the estimates: across the remaining twenty exclusions, β(LPI) ranges from 10.09 to 12.43 and remains significant at p < 0.02 throughout. Within the frontier, LPI varies only between 3.6 and 4.3, so the

Table 5. Robustness verification matrix

Test	Statistic/Estimate	95% CI/p–value	Interpretation
A. VIF, M2–M3 (max)	1.547	<5	No multicollinearity
B. Shapiro–Wilk, M3	W=0.965	p=0.622	Normal residuals
C. Breusch–Pagan LM	LM=128.9	p<0.001	Pooled OLS rejected
C. Hausman test	χ2=20.024, df=5	p=0.001	FE preferred over RE
C. Wooldridge AR(1)	F=29.7	p<0.001	DK–SE applied
D. FE: β(LPIc)	3.60 (SE=1.52)	p=0.042	Significant within countries
D. FE: β(ECIc)	–0.54 (SE=1.18)	p=0.651	Structural effect only
E. Bootstrap ACME (LPI)	7.585	[–0.581; 15.499]; p=0.124	CI includes 0 at n=21
E. Bootstrap ADE	8.781	[1.635; 15.226]; p=0.012	Direct effect significant
E. Total effect (c)	16.366	[2.663; 25.718]; p=0.008	Total confirmed
E. Proportion mediated	0.463	[–0.120; 0.786]; p=0.124	Matches BK estimate
F. M3 excl. Ireland, Hong Kong: β(LPI); R2	11.20; 0.731	p=0.008	Robust to outlier removal
G. Ukraine illustrative scenario, b2*ΔLPI	13.335*1.200=16.00 GII pts	–	Ceteris paribus; median LPI=3.87
H. M3 excl. Ukraine (n=20): β(LPI); R^2	7.611 (SE=4.734); 0.442	p=0.127	Significance lost
H. Excl. Ukraine: total effect c	8.465 (SE=4.179)	p=0.058	Marginal
H. Excl. Ukraine: path a_2 (ECI–LPI)	0.137 (SE=0.184)	p=0.467	Mediation link collapses
H. Excl. Ukraine: path b_2 (LPI–GII | ECI)	8.829 (SE=5.066)	p=0.099	Attenuated
H. Excl. Ukraine: indirect effect	1.209 (14.3% of c)	–	vs 7.585 (46.3%) full sample
H. Leave–one–out, other 20 exclusions: β(LPI)	10.09–12.43	all p<0.02	No other single–country influence

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identifying variation for the complexity–logistics link, and hence for the mediation chain, originates primarily in the contrast between the frontier and the catching-up economy in the sample.

Effect-size analysis (Table 6, Panel A) establishes LPI as the strongest predictor in M3: standardized β(LPI) = 0.491 (p = 0.005) versus β(ECI) = 0.449 (p = 0.010) and β(SW_{exp}) = 0.265 (p = 0.057); partial R^2 of 37.9% versus 33.4% and 19.6%; and the largest incremental contribution to fit (ΔR^2 = 0.159). Under HC3 robust standard errors (Panel B), β(LPI) and β(ECI) remain significant (p = 0.025 and p = 0.026), while β(SW_{exp}) becomes marginally non-significant (p = 0.092), consistent with the mediation finding.

The Breusch–Pagan test (Table 7) confirms homoscedasticity in all specifications (M3: BP = 1.987, p = 0.575), validating conventional OLS inference as the primary basis.

The pooled panel mediation estimation (Table 8) re-estimates the system on all 105 country-year observations with year fixed effects and country-clustered standard errors.

In the full sample, the total effect is c = 12.589 (p = 0.022); the paths are a2 = 0.526 (p = 0.055) and b2 = 12.464 (p < 0.001). The indirect effect equals 6.551 GII points, 52.0% of the total effect, corroborating the cross-sectional evidence with substantially more data. Excluding Ukraine, b2 remains highly significant (8.273, p < 0.001), while a2 falls to 0.201 (p = 0.136) and the indirect share declines to 25.1%. The stability of b2 across samples and specifications establishes that logistics performance robustly predicts innovation outcomes; the sensitivity of a2 establishes that the transmission from complexity to logistics, and hence the mediated share, is identified by the development gap.

4. DISCUSSION

The results yield three theoretically significant findings. The logistics performance emerges as the principal candidate mediator in the Economic Complexity Index (ECI)–Global Innovation Index (GII) system. The cross-sectional indirect effect equals 7.585 GII points (46.3% of the total effect), and the pooled panel estimate equals 6.551 points (52.0%), although the bootstrap confidence inter-

Table 6. Effect size analysis and robust SE comparison (M3, n = 21)

Variable	Std. β	p (OLS/HC3)	Partial R^2	Incremental ΔR^2
ECI	0.449	0.010/0.026	0.334 (33.4%)	0.446 (M1 alone)
SWexp	0.265	0.057/0.092	0.196 (19.6%)	+0.135 (M1→M2)
LPI	0.491	0.005/0.025	0.379 (37.9%)	+0.159 (M2→M3)

Note: Std. β – standardized OLS coefficient (z-score method). Partial R2 – unique variance explained after controlling for the other predictors. HC3 – heteroscedasticity-consistent standard errors.

Table 7. Breusch–Pagan homoscedasticity test: OLS Models M1–M3 (n = 21, 2024)

Model	BP Statistic	Df	p-value
M1 (ECI only)	1.343	1	0.247
M2 (ECI + SWexp)	2.167	2	0.338
M3 (ECI + SWexp+LPI)	1.987	3	0.575

Note: H_0: homoscedasticity (constant error variance). Rejection at p < 0.05 would indicate heteroscedasticity requiring robust SE. All three models retain H_0, validating conventional OLS inference.

Table 8. Pooled panel mediation estimation, 2020–2024 (year fixed effects; country-clustered SE)

Parameter	Full sample (n=105)	Excluding Ukraine (n=100)	Interpretation
M3: β(ECI)	8.068 (p=0.008)	7.014 (p=0.021)	Complexity effect robust
M3: β(SW_{exp})	7.433 (p=0.011)	7.839 (p=0.001)	Conditional direct association
M3: β(LPI)	10.464 (p<0.001)	5.818 (p=0.059)	Attenuated within frontier
M3: R^2	0.712	0.484	–
Total effect c	12.589 (p=0.022)	6.615 (p=0.058)	–
Path a_2 (ECI–LPI)	0.526 (p=0.055)	0.201 (p=0.136)	Identified by development gap
Path b_2 (LPI–GII | ECI)	12.464 (p<0.001)	8.273 (p<0.001)	Robust in both samples
Indirect effect (share of c)	6.551 (52.0%)	1.659 (25.1%)	Mediation gap–driven

val includes zero at $n = 21$, so the mediation evidence is suggestive rather than confirmatory. This finding is consistent with the theoretical arguments of Negi (2024) on logistics as an operational competitiveness factor and Wang et al. (2024) on supply chain integration. This constitutes the first country-level quantitative assessment of logistics performance index (LPI) as a mediator of the productive complexity-innovation link. The mechanism is coherent. More complex productive structures require, and tend to develop, more efficient logistics systems; logistics efficiency, in turn, facilitates knowledge diffusion, reduces R&D location barriers for multinational firms, and lowers the coordination costs of complex production.

The sensitivity and influence analyses, however, reframe the locus of this mediation. Within the innovation frontier, logistics performance is uniformly high (LPI between 3.6 and 4.3), and the ECI–LPI path is flat. Frontier economies have already saturated the logistics channel, so marginal differences in complexity no longer translate into logistics differentials. The identifying variation for the mediation chain originates in the joint deficit of the catching-up economy in the sample. Ukraine combines the lowest complexity (ECI = 0.359) with the weakest logistics (LPI = 2.70), and it is this development contrast that the mediation estimates capture. The pooled panel supports this assumption. The LPI–GII path is robust in every sample and specification ($p < 0.001$), whereas the complexity–logistics path weakens once Ukraine is excluded. The substantive conclusion is therefore not that logistics mediates complexity within advanced economies, but that the logistics channel constitutes the margin along which catching-up economies convert, or fail to convert, productive complexity into innovation capacity.

The second finding is that software expenditure (SW_{exp}) does not mediate ECI–GII in the Baron–Kenny sense, contrary to the widely held view that digital capital expenditure is the primary amplifier of productive complexity. This result is consistent with the "digitalization paradox" documented by Wu et al. (2025), who find that returns to IT investment depend critically on the specificity of existing resources and the depth of operational integration. At the country level, raw software expenditure as a share of GDP appears to be an imperfect proxy for digitally enabled productive capacity, particularly for complex economies where a larger GDP denominates the ratio downward. The implication is that ICT expenditure data, while widely available, may be a misleading guide to the digital channel of innovation.

The third finding, within-R^2 = 0.056 in the FE specification, establishes that the ECI–GII path operates on a structural rather than cyclical time scale, in line with Karbevska and Hidalgo (2025) on the deeply embedded, slow-changing nature of global value chains centrality patterns. Short-term within-country fluctuations in ECI partly reflect composition effects of export baskets and transitory movements in commodity prices or trade volumes unrelated to genuine changes in productive complexity; the within-estimator differences outweigh the stable between-country variation, which is why $\beta(ECI_c)$ is statistically indistinguishable from zero while $\beta(LPI_c) = 3.60$ remains significant. The policy corollary is that structural transformation of productive capacity, rather than annual marginal changes in ECI, is the operative mechanism, and that changes in logistics efficiency are the more temporally responsive within-country margin.

For Ukraine, the results carry a specific strategic implication, which we present as an illustrative arithmetic scenario. With LPI = 2.70 and ECI = 0.359, the country faces a compounded disadvantage. The structural complexity deficit constrains the total effect, while the logistics gap reduces the transmitted share. Multiplying the cross-sectional coefficient b_2 by Ukraine's LPI gap to the sample median yields approximately 16 GII points (Table 5, Panel G). This figure translates the estimated coefficients into policy-relevant units under a strict ceteris paribus assumption. It is not a counterfactual policy estimate, since the coefficient is estimated on 21 economies, the design is observational, and the mediation effect is not confirmed by the bootstrap. Read in this spirit, and jointly with the development-gap interpretation above and the within-country responsiveness of LPI, the scenario suggests that logistics reform, customs digitalization, transport infrastructure restoration, and traceability standards are a policy margin for which innovation returns may materialize on a shorter horizon than the structural adjustment of export complexity.

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CONCLUSION

The objective of this study is to test whether logistics performance mediates the relationship between economic complexity and national innovation performance in a sample of innovation-frontier economies and Ukraine over 2020–2024. Three findings emerge. First, the logistics channel is supported by cross-sectional point estimates (indirect effect of 7.585 GII points, 46.3% of the total effect) and corroborated by pooled panel estimation (6.551 points, 52.0%). However, sensitivity analysis shows the channel is identified by the development contrast between the frontier and Ukraine rather than by variation within the frontier, and the bootstrap does not confirm the indirect effect at the available sample size. Second, the software-expenditure channel fails the mediation conditions, cautioning against equating digital spending ratios with digitally enabled innovation capacity. Third, the complexity–innovation relationship is predominantly structural between countries, while logistics performance remains the more temporally responsive within-country margin. Thus, logistics infrastructure deserves consideration as a first-order policy margin specifically for catching-up economies, for which the channel is not yet saturated; the mediation hypothesis warrants replication on a broader panel spanning the full development distribution before informing quantitative policy targets.

Five limitations condition these conclusions. First, the biennial publication cycle of LPI requires within-wave carry-forward, attenuating within-country LPI estimates and rendering the FE results conservative. Second, the sample of 21 economies limits statistical power, in particular for mediation inference, as the bootstrap analysis makes explicit, and for detecting non-linearities. Third, the frontier-plus-Ukraine design implies that the findings characterize transmission at the innovation frontier and its contrast with a catching-up economy; they cannot be generalized to the full distribution of countries, and the influence analysis shows the mediation chain is identified primarily by that contrast. Fourth, the Baron–Kenny procedure does not formally identify causal order; instrumental variables or quasi-experimental designs are recommended for future work. Fifth, extensions to a broader panel incorporating middle-income economies are required to assess whether the mediation asymmetry and the development-gap identification generalize beyond the present sample.

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APPENDIX A

Table A1. Dataset

Country	Year	GII	ECI	SW_{exp}	HT_{exp}	GDP_{gr}	LPI
Switzerland	2020	66.1	1.725	0.67	12.85	–3	3.9
Switzerland	2021	65.5	1.736	0.71	14.24	4.8	3.9
Switzerland	2022	64.6	1.749	0.71	29.99	2.2	4.1
Switzerland	2023	67.6	1.773	0.68	29.33	–0.6	4.1
Switzerland	2024	67.5	1.584	0.65	29.27	0	4.1
Sweden	2020	62.5	1.375	0.51	15.14	–2.9	4.05
Sweden	2021	63.1	1.386	0.7	13.93	4.6	4.05
Sweden	2022	61.6	1.37	0.8	17.26	0.6	4
Sweden	2023	64.2	1.373	0.71	17.62	–0.7	4
Sweden	2024	64.5	1.236	0.68	17.65	0.5	4
The USA	2020	60.6	1.323	1.09	19.49	–2.8	3.89
The USA	2021	61.3	1.274	1.25	19.9	5.9	3.89
The USA	2022	61.8	1.304	1.25	20.58	1.9	3.8
The USA	2023	63.5	1.232	1.33	21.85	2	3.8
The USA	2024	62.4	1.122	1.26	24.32	1.8	3.8
Singapore	2020	56.6	1.672	0.25	55.26	–3.9	4
Singapore	2021	57.8	1.664	0.26	54.97	14.4	4
Singapore	2022	57.3	1.651	0.25	56.83	0.7	4.3
Singapore	2023	61.5	1.679	0.23	56.14	–3	4.3
Singapore	2024	61.2	1.52	0.21	59.43	2.3	4.3
The United Kingdom	2020	59.8	1.293	0.51	23.01	–9.4	3.99
The United Kingdom	2021	59.8	1.378	0.69	23.82	8.2	3.99
The United Kingdom	2022	59.7	1.397	0.74	27.16	4.2	3.7
The United Kingdom	2023	62.4	1.379	0.62	28.89	–1	3.7
The United Kingdom	2024	61	1.246	0.56	29.72	0.1	3.7
Finland	2020	58.1	1.376	0.44	9.98	–2.8	3.97
Finland	2021	58.4	1.356	0.57	10.29	2.5	3.97
Finland	2022	56.9	1.328	0.64	9.62	0.5	4.2
Finland	2023	61.2	1.3	0.6	9.71	–1.4	4.2
Finland	2024	59.4	1.146	0.59	9.29	–0.2	4.2
Denmark	2020	57.1	1.052	0.51	13.23	–2.2	3.99
Denmark	2021	57.3	1.056	0.65	13.92	6	3.99
Denmark	2022	55.9	1.025	0.7	15.99	–0.3	4.1
Denmark	2023	58.7	1.041	0.64	17.13	–0.1	4.1
Denmark	2024	57.1	1.012	0.62	17.62	3	4.1
The Netherlands	2020	58.3	1.002	0.51	23.16	–3.9	4.02
The Netherlands	2021	58.6	1.01	0.66	22	5.7	4.02
The Netherlands	2022	58	0.999	0.73	21.96	4	4.1
The Netherlands	2023	60.4	0.993	0.57	23.79	–1.6	4.1
The Netherlands	2024	58.8	0.948	0.54	23.47	0.4	4.1
South Korea	2020	56.1	1.78	0.21	35.6	–0.7	3.61
South Korea	2021	59.3	1.77	0.26	36.01	4.7	3.61
South Korea	2022	57.8	1.774	0.29	36.12	2.9	3.8
South Korea	2023	58.6	1.724	0.27	30.28	1.5	3.8
South Korea	2024	60.9	1.6	0.26	36.26	1.9	3.8
Germany	2020	57	1.507	0.47	15.5	–3.8	4.2
Germany	2021	57.3	1.519	0.6	15.39	3.9	4.2
Germany	2022	57.2	1.521	0.66	17.5	1.8	4.1
Germany	2023	58.8	1.499	0.49	17.78	–1	4.1
Germany	2024	58.1	1.356	0.48	17.98	–0.8	4.1
France	2020	52.8	1.212	0.53	23.23	–7.9	3.84
France	2021	55	1.213	0.66	21.92	6.5	3.84

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Table A1 (cont.). Dataset

Country	Year	GII	ECI	SW_{exp}	HT_{exp}	GDP_{gr}	LPI
France	2022	55	1.179	0.67	22.98	2.2	3.9
France	2023	56	1.175	0.63	23.68	1.2	3.9
France	2024	55.4	1.087	0.61	23.14	0.9	3.9
China	2020	53.3	1.341	0.3	31.28	2.1	3.61
China	2021	54.8	1.384	0.32	30.22	8.5	3.61
China	2022	55.3	1.361	0.33	27.77	3.1	3.7
China	2023	55.3	1.348	0.34	26.57	5.5	3.7
China	2024	56.3	1.271	0.33	26.28	5.1	3.7
Japan	2020	54.2	2.005	0.26	18.63	–4	4.03
Japan	2021	54.5	2.021	0.3	18	3.2	4.03
Japan	2022	53.6	1.993	0.32	18.26	1.4	3.9
Japan	2023	54.6	1.916	0.31	17.1	2	3.9
Japan	2024	54.1	1.729	0.33	17.55	0.5	3.9
Israel	2020	50	1.215	0.24	28.2	–1.4	3.31
Israel	2021	53.4	1.248	0.25	29.6	7.6	3.31
Israel	2022	50.2	1.233	0.24	29.11	4.2	3.6
Israel	2023	54.3	1.174	0.25	34.94	–1.2	3.6
Israel	2024	52.7	1.334	0.24	37.23	–0.4	3.6
Canada	2020	52.8	0.894	0.62	16.76	–5.1	3.73
Canada	2021	53.1	0.858	0.68	16.34	5.4	3.73
Canada	2022	50.8	0.867	0.67	15.15	2.3	4
Canada	2023	53.8	0.826	0.65	16.37	–1.4	4
Canada	2024	52.9	0.778	0.63	16.78	–1.4	4
Hong Kong	2020	54.2	1.295	0.36	69.65	–6.5	3.92
Hong Kong	2021	53.7	1.352	0.39	70.55	7.4	3.92
Hong Kong	2022	51.8	1.303	0.38	72.64	–2.8	4
Hong Kong	2023	53.3	1.298	0.39	72.32	0.6	4
Hong Kong	2024	50.1	1.162	0.36	75.57	2.7	4
Estonia	2020	50	1.025	0.14	20.62	–2.9	3.31
Estonia	2021	49.9	1.046	0.15	20.63	8.1	3.31
Estonia	2022	50.2	0.994	0.14	18.02	–2.5	3.6
Estonia	2023	53.4	0.982	0.12	16.58	–4.3	3.6
Estonia	2024	52.3	0.89	0.12	18.38	–0.2	3.6
Austria	2020	50.1	1.364	0.51	12.27	–6.5	4.03
Austria	2021	50.9	1.369	0.65	11.02	4.5	4.03
Austria	2022	50.2	1.362	0.69	14.91	4.3	4
Austria	2023	53.2	1.37	0.58	15.92	–1.8	4
Austria	2024	50.3	1.249	0.57	18.45	–1.2	4
Ireland	2020	50.3	1.221	0.63	25.9	5.8	3.51
Ireland	2021	50.7	1.23	0.71	28.48	14.6	3.51
Ireland	2022	48.5	1.297	0.75	46.79	5.4	3.6
Ireland	2023	50.4	1.229	0.7	47.77	–4.3	3.6
Ireland	2024	50	1.193	0.68	53.52	1	3.6
Norway	2020	51.1	0.97	0.48	22.07	–0.7	3.7
Norway	2021	50.4	0.854	0.64	20.59	3.4	3.7
Norway	2022	48.8	0.786	0.6	23.88	2.3	3.7
Norway	2023	50.7	0.732	0.61	25.67	–1.1	3.7
Norway	2024	49.1	0.726	0.61	25.41	1.1	3.7
Ukraine	2020	37.4	0.59	0.51	5.85	–3.7	2.83
Ukraine	2021	35.6	0.537	0.46	4.51	4.4	2.83
Ukraine	2022	31	0.509	0.58	5.74	–22.7	2.7
Ukraine	2023	32.8	0.447	0.49	6.69	15.4	2.7
Ukraine	2024	29.5	0.359	0.42	6.37	2.5	2.7