BEYOND DIVERSIFICATION: HOW INNOVATION TRANSLATES INTO ECONOMIC COMPLEXITY IN UKRAINE

by

Ivan Suprun

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Thesis Supervisor: Dmytro Krukevets, PhD, Faculty of Social Sciences

Approved by ____

Head of the KSE Defense Committee, Professor

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Date _____________________________________

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LIST OF ABBREVIATIONS

ECI — Economic Complexity Index

EIS — European Innovation Scoreboard

EU — European Union

EXPY — Export Sophistication Index

FDI — Foreign Direct Investment

FE — Fixed Effects

GDP — Gross Domestic Product

GII — Global Innovation Index

ICT — Information and Communication Technology

LM Test — Lagrange Multiplier Test

MON — Ministry of Education and Science of Ukraine

OECD — Organisation for Economic Co-operation and Development

OLS — Ordinary Least Squares

PPP — Purchasing Power Parity

R&D — Research and Development

TWFE — Two-way Fixed Effects

WIPO — World Intellectual Property Organization

ABSTRACT

The 2025 Nobel Prize-winning work in Economic Sciences has renewed attention to sustained growth and the central role of innovation in achieving it. For Ukraine, this raises a practical question for post-war recovery: can stronger innovation capacity be translated into expanded production and greater export sophistication through industrial policy, or will it remain isolated from deeper structural transformation? The capstone research examines the relationship between innovative performance and economic complexity scores, determining the strength of this connection across different economies and testing whether it is weakened in low-support environments (e.g., weak R&D investment and limited firm collaboration). Existing research and policy reports primarily emphasize that R&D spending, human capital, and institutions are the key drivers of innovation and, consequently, productivity. At the same time, the 2024 European Innovation Scoreboard indicates that Ukrainian SMEs continue to exhibit very low levels of product and process innovation, despite continuous reforms. Empirically, the thesis constructs a panel dataset covering Ukraine, selected European countries, and other advanced economies. It combines Economic Complexity Index components with the Global Innovation Index (GII) and its pillars, and the European Innovation Scoreboard (EIS) outcomes, alongside supporting variables related to economic sophistication, as controls and interaction terms in regression analysis. The current government's focus, as outlined in the Government Action Plan, emphasizes increasing production and enhancing export complexity. This goal is supported by the National Export Strategy to 2030 and by economic support programs, such as capital expenditure tax exemptions, which aim to achieve it. Findings will guide whether to push into higher-value products or first strengthen skills, research, and firm–university links, thereby supporting the alignment of industrial and innovation policies in the context of post-war recovery and EU integration.

1. Introduction

1.1 PROBLEMATICS AND RELEVANCE

Ukraine's National Export Strategy to 2030 has set a direct and ambitious plan – to enhance the resilience of the economy, strengthen its technological potential, and transition to export-oriented growth with more value added to goods and services produced. The strategy sets measurable targets, for instance, raising exports to up to $77 billion and increasing exports to 33% of GDP, but early indicators point to binding constraints in the innovation system (Ministry of Economy, Environment, and Agriculture of Ukraine). In the European Innovation Scoreboard 2024 country profile, Ukraine is classified as an "Emerging Innovator," with performance 32.5% below the EU average, and SME innovation is flagged as one of the country's key relative weaknesses (European Commission 3). Alongside that report directly emphasizes Innovation in the SME sector as a relative weakness, with only 5.9% of SMEs introducing process innovations and 4.4% introducing product innovations (2022) (European Commission 5). The situation is worsened by the increasing brain drain trend since 2017, with a decline in the number of doctor graduates and in R&I human resources (The Global Economy). The result is a strategic paradox: Ukraine's export strategy aims to climb toward higher value-added, more complex production, but the indicators show that the firm-level innovation capacity, especially among SMEs, remains exceptionally weak, raising the core question of how innovation-system conditions may support, constrain, or remain disconnected from the development of more complex economic structures (Ministry of Economy of Ukraine; European Commission 3, 5).

Alongside that, Ukraine already has a decent performance in the Economic Complexity Index, ranking 47th out of 132 on the scoreboard in 2025, indicating the presence of capacity for a sophisticated economy and export opportunities (The Observatory of Economic Complexity). Despite low-complexity items dominating Ukraine's exports due to structural and historical constraints that limit specialization in more advanced products, Ukraine's ICT services exports increased significantly, indicating potential capability upgrades across sectors despite overall weak goods-export complexity (Kyiv Global Government Technology Center).

The existing literature highlights a link between the sophistication of exports and levels of innovation, but from a slightly different perspective. The foundational complexity framework (Hidalgo and Hausmann) notes that a country's export structure hides the productive capabilities an economy can deliver, such that more complex economies should facilitate better knowledge to support higher levels of economic activity. Empirical studies reveal that, in the long run, there is evidence of a mutually reinforcing relationship between complexity and innovation when innovation is proxied by patents, though this approach may miss non-patented and incremental forms of innovation common in transition economies, especially for the case of institutional weakness for patent formation in Eastern European countries (Nguyen et al.) (European Commission 5). Other works describe broader systems of innovation, for instance, Araújo et al. prove that pillars of innovation development (infrastructure and business sophistication) are positively connected with complexity, while Du and O’Connor argue that changes in complexity reflect how efficiently national systems translate knowledge into productive outcomes, highlighting firm-level diffusion and SME dynamics rather than frontier R&D alone (Du and O'Connor 238). In general, the literature suggests that complexity may serve as the structural basis for innovation; however, the effectiveness of this translation relies on supportive conditions (R&D, institutions, infrastructure, and firm collaboration), and there is still insufficient direct examination of which dimensions of the innovation system are associated with different forms of economic complexity, especially in economies such as Ukraine.

This discrepancy motivates the main research question for this paper: Which innovation-system conditions are most strongly associated with different dimensions of economic complexity, and do comparable European countries exhibit stronger associations with these conditions than Ukraine does relative to its observed complexity? The uniqueness of this study lies in the operationalization approach of estimating the strength of these links. In addition to the use of R&D and patents in the model, it treats innovation as a multidimensional ecosystem outcome using composite measurements (GII), which explicitly balance innovation inputs and outputs, alongside the Economic Complexity Index as the main measure of economic performance sophistication. It then embeds Ukraine in a comparative European panel (2011–2024) to separate what is structural (the "productive knowledge" implied by export sophistication) from what is institutional and capability-based (R&D effort and related enabling conditions), consistent with the economic complexity view that "what countries make reveals what they know" (Hausmann et al. 22). This design allows to see whether Ukraine really underperforms innovatively relative to its complexity, as well as examine the similar cases, to then suggest potential policy visions and directions.

For Ukraine, it is especially important to examine the relationship empirically rather than presume it occurs automatically. Ukraine exemplifies a strong case for the innovation–complexity relationship, as conventional complexity metrics are based on goods-export frameworks, whereas some of Ukraine's most vibrant capability indicators in recent years have emerged in ICT services, and wartime disruption can further separate production structure from innovation outcomes. Thus, the article reviews the complexity-innovation relationship as conditional: complexity may provide the capability base, but the conversion into innovation performance depends on enabling inputs such as R&D investment and diffusion capacity within firms, which is an institutional task for Ukraine. Additionally, the analysis uses a comparative panel with country- and year-fixed effects, allowing the study to separate time-invariant structural differences across countries from changes over time, thereby strengthening the credibility of cross-country benchmarking for Ukraine.

1.2 RESEARCH QUESTIONS AND HYPOTHESES

The main question that research aims to answer is “Does increasing innovative performance lead to higher economic complexity in Ukraine and comparable European economies?” Additionally, the paper asks whether Ukraine's innovative performance compares with that of countries with similar economic complexity levels in the European region, and whether these findings can inform policy-making propositions.

Hypotheses include:

H1: Countries with stronger innovation-system conditions tend to exhibit higher levels of economic complexity.

H2: The significance of different GII sub-pillars and control variables varies across ECI dimensions.

H3: Ukraine exhibits weaker innovation-system performance than comparable European countries relative to its observed level of economic complexity.

Chapter 2. Literature Review

Before examining how the innovative measures are linked to economic complexity, it is crucial to define and explain what economic complexity actually is. In the work of Hidalgo and Hausmann, Atlas of Economic Complexity (2014), when defining economic complexity and explaining the introduction of the Economic Complexity Index (ECI) as a way to measure it, the authors directly emphasize the connection between the knowledge society holds and its development, which essentially can be linked to complexity. (Hidalgo 15-18). The concept of economic complexity is based on diversity and ubiquity. Diversity amplifies the range of a country's production, while ubiquity represents the amount of knowledge needed to produce a certain product. Combined, they are "crude approximations of the variety of capabilities available in a country or required by a product" (Hidalgo 20). Each of the measures can be used to correct the others, thus converging and representing the true quantitative measure of economic complexity for an economy. This makes economic complexity empirically one of the most diverse measures for capturing the performance of economies. The empirical strength of the measure is also reflected in its explanatory capacity. In the Atlas of Economic Complexity, the ECI explains a very large share of cross-country variation in income per capita, accounting for about 75% of the variance among countries with limited natural-resource dependence and around 73% after controlling for natural-resource income more broadly (Hidalgo 27-29). Therefore, the Economic Complexity Index has the capacity to be used as a strong complex measure of evaluation of a country`s competitive strength on the global market and general assessment of its economic performance and capacity for growth.

Hidalgo further develops this perspective by showing that economic complexity matters not only as a measure of productive sophistication but also as a broader framework through which information, capabilities, institutions, and industrial structures interact to shape economic growth. Cesar Hidalgo assesses the importance and influence of economic complexity on the spread of information in his work “Why Information Growth.” When explaining the growth of economies through the expansion of information, the author emphasizes that industries constitute the structure that enables collective progress, including knowledge and know-how (Hidalgo 142). In this view, industries are important because they act as structures that store and coordinate the capabilities required for sophisticated production, while the presence of related industries increases the likelihood that new activities can emerge successfully. Hidalgo also mentions that exports, as part of economic complexity, “can tell us about not only know-how and knowledge and the diversity of physical capital, but also about the quality of the formal institutions involved”, which establishes a relationship framework between institutions and economic sophistication and growth (Hidalgo 155). At the same time, Hidalgo’s argument implies that the innovative capabilities alone are not enough to bring more sophistication to the economy, since the translation of productive knowledge into new outcomes depends on the supporting structures through which knowledge is diffused, combined, and applied.

In academic writings, innovation is viewed not as a solitary groundbreaking concept, but as an extensive occurrence that encompasses what is produced, the method of its development, and the structural circumstances enabling it. Kenneth Kahn contends that innovation must be characterized in three interrelated ways: as an outcome, as a process, and as a mindset. Consequently, innovation signifies the launch of something novel or enhanced, encompassing not just products but also processes, marketing strategies, business models, supply chains, and organizational structures. Innovation is a process that encompasses the organized journey through which ideas are identified, cultivated, and brought into practical application. As a mentality, it embodies a culture and perspective that promotes experimentation, collaborative work across different functions, continuous learning, and receptiveness to change. Kahn emphasizes that innovation isn't confined to disruptive breakthroughs, as gradual enhancements are also integral to innovation and frequently vital for sustained success (Kahn 453-459). This definition aligns closely with the idea of the Global Innovation Index (GII), as the GII views innovation not merely as an individual invention or patent, but rather as a more extensive national ability to produce, nurture, and implement new concepts. In this regard, Kahn's definition clarifies why the GII reflects innovation as both capacity and outcome, instead of merely as singular technological novelty.

While these works provide a strong conceptual basis for linking innovative driving capabilities and complexity, the empirical literature tests this relationship using specific approximations.

As outlined in the theoretical literature, other scholars stress that economic complexity alone does not guarantee strong innovation performance. Du and O`Connor (2021) in "Examining economic complexity as a holistic innovation system effect" argue that changes in economic complexity reflect the efficiency of national innovation systems in transforming knowledge into productive outputs. Authors describe it as a holistic innovation system in which knowledge-intensive and market-led innovations combine (Du and O`Connor 237). From this perspective, additional complexity growth relies not only on formal R&D but also on economies' capacity to merge market-driven innovation, entrepreneurial ventures, and knowledge-based skills into products that access export markets (Du and O`Connor 240–241). They show that countries where the spread of efficiency among companies and industries is faster experience quicker productivity growth and greater complexity. This then highlights the key roles of market-based innovation, entrepreneurship, and business structures, rather than only frontier R&D, pushing the literature beyond "complex exports are good" toward how capability transformation occurs. However, complexity does not grow automatically from inputs alone, and factors such as government expenditure or population size do not guarantee efficiency gains unless they are matched by stronger capability use and coordination (Du and O`Connor 247, 254). This leaves room for structural comparisons between the economies, where investigation can examine which innovation-system conditions support the conversion of productive knowledge into greater complexity, and why.

Recent empirical research has tried to show how innovation and economic complexity are connected, while also raising important questions about how innovation should be measured across countries. “The drivers of economic complexity: International evidence from financial development and patents” by Nguyen et al. (2020) finds a bidirectional long-run relationship between economic complexity and innovation output, as measured by patents, and includes various indicators of financial development. However, its panel estimates primarily emphasize the direction from patenting to complexity, finding that higher patent activity (especially resident patents) is associated with higher ECI/ECI+ levels (Nguyen et al. 145-148). At the same time, the study is useful because it highlights a measurement limitation central to the present paper, since patents capture only a relatively narrow, formalized dimension of innovation. This leaves open the question of whether broader innovation-related indicators, beyond patents alone, can also help explain cross-country differences in economic complexity. The measurement issue is particularly relevant for Ukraine, since the European Commission’s European Innovation Scoreboard country profile notes weak “Intellectual assets”. That includes a decline in patent applications since 2017 (European Commission 5), while the World Intellectual Property Organization statistical profile reports comparatively low resident patent applications per million inhabitants (World Intellectual Property Organization 1). The present study helps to examine this relationship using composite innovation measures alongside patents and to investigate which components are most influential on it.

Araujo et al. (2025) directly examine the relationship between economic complexity and the pillars of national innovation systems in their study “The relationship between the pillars of national innovation systems and economic complexity: An international empirical analysis,” using data for 112 countries in 2020. Their main argument is that economic complexity does not emerge automatically but depends on coordinated innovation-system conditions, as captured by the Global Innovation Index input pillars. Findings demonstrate the importance of the relationship between infrastructure and business sophistication, with a positive, significant impact on economic complexity. They specifically state that prioritizing them will strengthen the overall innovation system. Authors also state that “countries that adopt flexible, forward-looking policies may be better equipped to navigate the complexities of global competition and technological advancement", thus suggesting that countries must not only possess knowledge but also have the capacity to apply and scale it (Araujo et al. 19). This study is important because it provides direct evidence that some innovation-system components are more closely linked to complexity outcomes than others, but its design remains cross-sectional and centered on a single aggregate ECI measure. However, unlike this study, the present paper uses a panel-based approach to examine whether these relationships remain stable over time, differ across dimensions of complexity, and help explain Ukraine's position relative to comparable European economies.

Based on the literature review, it can be concluded that economic complexity is best understood as a capability-based approach that reflects how effectively innovative-supportive measures are implemented by economies, but it does not arise automatically from the existence of others. Whether innovation converts into complexity depends on complementary conditions – most consistently highlighted are R&D effort, infrastructure, and business environment quality, access to finance, and the capacity of firms (especially SMEs) to absorb, adapt, and scale new knowledge. At the same time, the empirical evidence remains uneven. Some studies use narrow, direct proxies, such as patents or financial markets, while others use a wide range of economic development instruments, and only a few use the pillars of the innovation system with economic complexity directly. Such empirical designs are often less suited for examining specific cases in detail, such as the Ukrainian one. Against this background, the present study examines how broader innovation-system conditions and supportive conditions are associated with different dimensions of economic complexity in a comparative European panel. In doing so, it aims to move beyond simple aggregate relationships and provide evidence on which specific innovation mechanisms matter most for structural upgrading and policy design.

Chapter 3. Data and Methodology

This study uses the country-year panel for European economies, including Ukraine, to examine how innovative performance measures are associated with different dimensions of economic complexity. The empirical design is constructed so that innovation is treated not just as a simple measure that influences the sophistication of the economy, but rather as a composite of factors that define innovative performance and further economic complexity. For that reason, the research uses four Economic Complexity Index (ECI) dimensions as dependent variables and uses the Global Innovation Index (GII), its sub-pillars and indicators, and additional controls as explanatory variables. This allows the analysis to become more detailed and deep in its empirical examination of which parts of the innovation system are most closely related to changes in economic complexities of different types across both countries and time. The choice also aligns with the examined literature, which treats scientific, technological, and industrial capabilities as related but analytically distinct domains rather than as a single, uniform national attribute.

The dependent variables of the research are four dimensions of the Economic Complexity Index (ECI): ECI Trade, ECI Technology, ECI Research, and ECI Software. These measures are designed as a multidimensional approach to examining how trade, technology, research capacity, and software link a country's diversity and sophistication of activities to the underlying capabilities embedded in the economy (Stojkoski et al. 2). The work of the World Intellectual Property Organization (WIPO) on multidimensional complexity also emphasizes the that scientific publications, patents, and trade provide great facilitation on capability accumulation and usage (Hausmann et al. 30 -31). Within this context, research complexity captures scientific capabilities, technological complexity reflects inventive and patent-related efforts, and trade complexity reflects industrial production capability. All of these outcomes help to capture the broad picture of layers of the innovation and development process and therefore justify separate model specifications. The distinction between types of complexity creates more room for significance in the analysis and a greater potential for higher-quality interpretations and policy suggestions.

The main explanatory variables are drawn from the Global Innovation Index (GII). The GII is particularly suitable for this study because it is not limited to a single aggregate innovation score. Instead, it is divided into Input and Output sub-indices, which help create a complex picture of how innovation is measured in the economy. It is designed to capture pillars and sub-pillars, each consisting of specific indicators that, in turn, composite into a general score and rank for a given economy in the GII. That structure allows selection of variables that correspond to specific mechanisms rather than relying solely on a single broad measure of innovation performance. Just as the distinction between types of economic complexity is crucial to the study, the breakdown of the Global Innovation Index is equally crucial. Hence, it details how particular conditions are associated with specific complexity outcomes.

Specific attention should be paid to the specifics of the use of GII data. WIPO explicitly warns against direct year-to-year comparison of GII rankings and even of simple scores without attention to methodological context (WIPO, GII 2024 Economy profiles). The first reason is the change in the composition of the indicator over time, which affects the significance of the annual results' reflection of underlying performance. In a panel study, this means historical GII data must be handled with care. To avoid biases and inconsistencies noted in the overall GII scores, the paper uses detailing with pillars and indicators as mentioned above. Despite not fully avoiding some methodology changes, recalculations, data drifts, or missing values, this paper constructs a common panel from official GII data tables and uses sub-pillar series that match each ECI dimension.

Additional control variables are drawn from the general characteristics of economic complexity and aim to predict its effectiveness or serve as additional inputs beyond those included in the GII. The main control pool consists of GDP per capita, high-technology exports (% of manufactured exports), manufacturing value added, individuals using the Internet (% of population), and foreign direct investment net inflows (% of GDP). All of them can be associated with differences in economic complexity across countries and over time.

The empirical sample is restricted to European economies that are consistently observed in the ECI files and linked to the GII and World Bank. The panel's time coverage is 2011–2024, subject to variable-specific availability (World Intellectual Property Organization). However, despite all the links and balances, the data is not ideal in terms of completeness. In practice, the final dataset is unbalanced; missing entries are reported as NA and not treated as zeros during aggregation. Following that logic, this paper does not create artificial observations in the baseline data. Country-year values that cannot be recovered from official sources are left missing rather than interpolated ad hoc.

The final dataset was constructed using the original datasets of ECI types, multiple yearly reports of GII, and the World Bank variables. The resulting panel dataframe is built by joining all the source files into a common long format, ensuring that every source shares the same merge keys of country code and year. The cleaning of the data prior to that ensures that models used later receive only variables with substantial data, and that non-numeric placeholders are converted to missing values. After all of the transformations, merging, and cleaning, the final dataset in use follows such a structure:

Table 1. Final dataset structure.

Variable label	Unit	Non-missing country-years	Coverage (%)	First year	Last year
ECI Research	index	400	73.3	2011	2023
ECI Technology	index	333	61.0	2011	2021
ECI Software	index	155	28.4	2020	2024
ECI Trade	index	434	79.5	2011	2024
GII rank	rank	544	99.6	2011	2024
GII score	0–100 score	544	99.6	2011	2024
EXPY mean	index	546	100.0	2011	2024
EXPY median	index	546	100.0	2011	2024
EXPY SD	SD across partners	546	100.0	2011	2024
EXPY partner	count	546	100.0	2011	2024

count					
GDP PPP mean	PPP level	546	100.0	2011	2024
R&D expenditure (% GDP)	%	453	83.0	2011	2023
Researchers in R&D (per million)	per million	363	66.5	2011	2023
FDI net inflows (% GDP)	%	541	99.1	2011	2024
Manufacturing value added	USD	546	100.0	2011	2024
Internet users (% of population)	%	540	98.9	2011	2024
High-tech exports (% of manufactured exports)	%	413	75.6	2011	2024

Source: Created by the author based on the data downloaded from GII, ECI, World Bank, and World Intellectual Property Organisation.

The dynamics of data for ECI and GII are represented graphically in Figures 1 and 2.

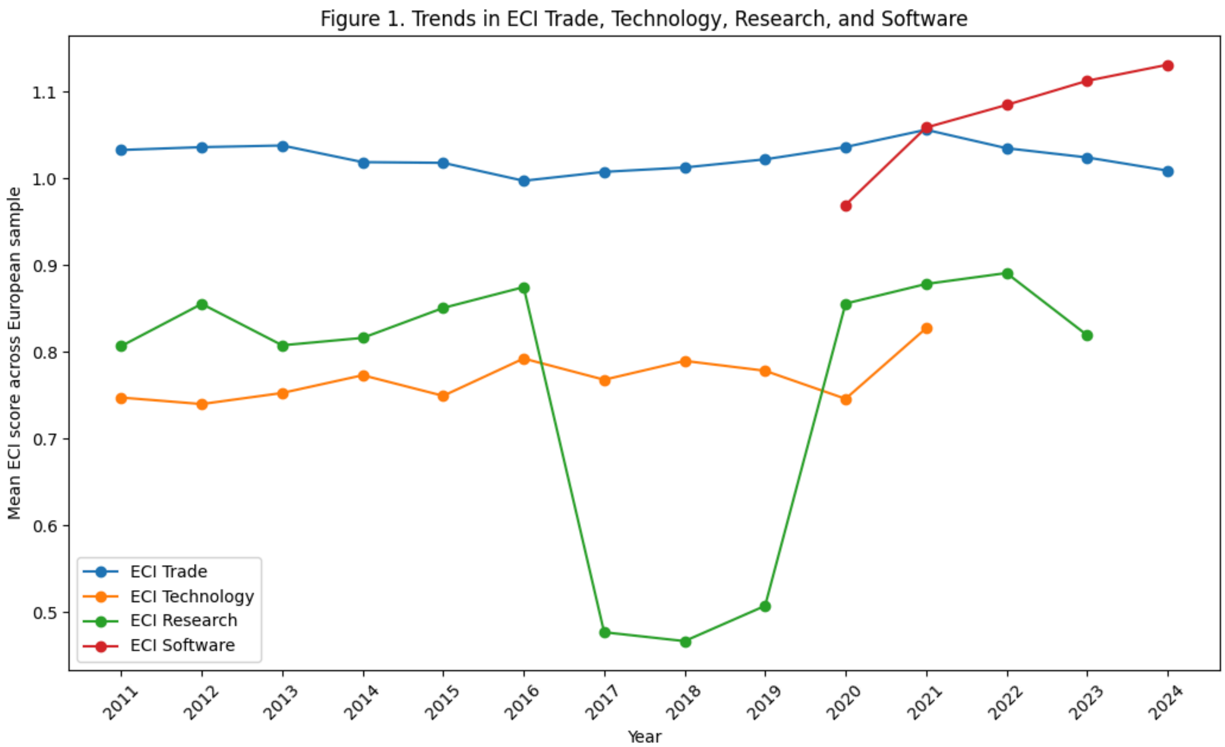

Figure 1. Trends in ECI Trade, Technology, Research, and Software; created by author based on ECI data.

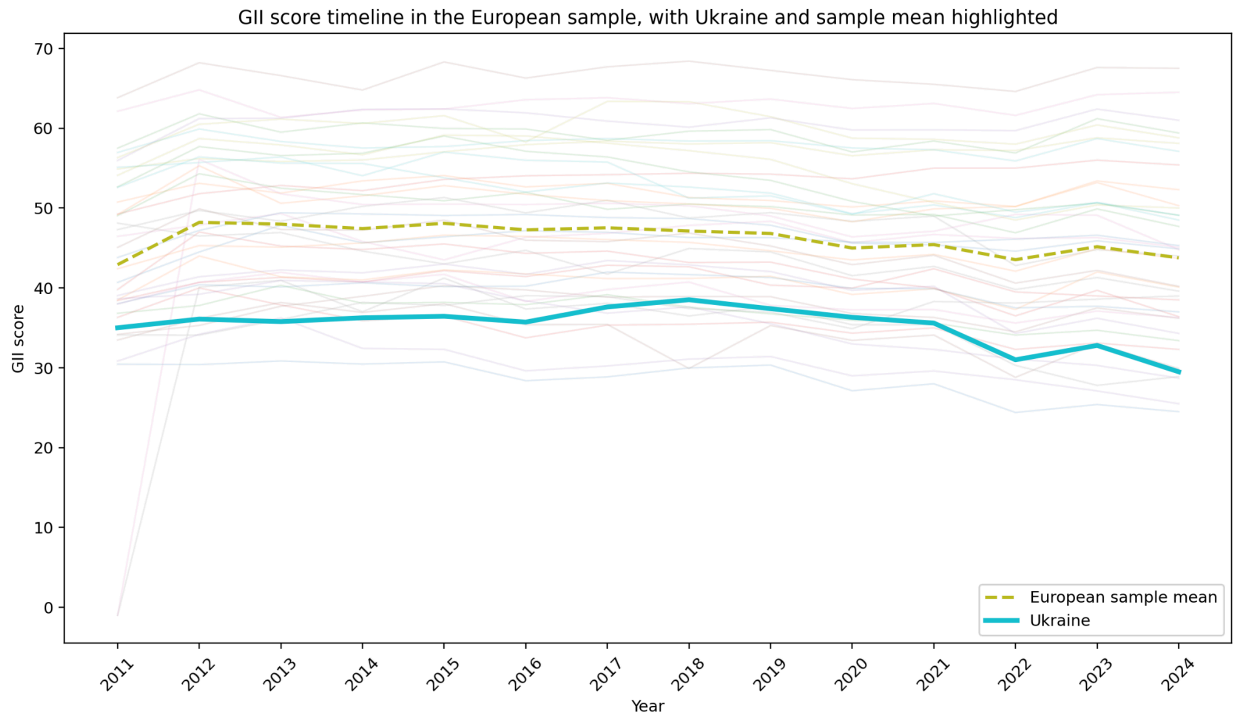

Figure 2. GII score timeline in the European sample, specifically Ukraine; created by author based on the GII data.

Figure 1 visualizes some of the features and limitations of the ECI dimensions. The technology series ends in 2021, the software series begins only in 2020, and the research series exhibits a marked temporary decline in 2017-2019, which creates greater amplitude in the data. The drop should be interpreted cautiously because ECI Research depends on bibliometric publication data. Therefore, changes in the coverage or classification of indexed publications, for example, in Scopus or a similar publication database, may have affected country-level research complexity scores independently of real changes in national research capacity. This confirms the concerns and provides an additional stimulus to test the empirical design model, to determine the complexity-innovation link. Figure 2 suggests that Ukrainian innovative measures remain well below much of the European sample, supporting the idea that there is room for improvement.

Empirical analysis uses three main types of models to test the significance of ECI links with different predictors: a pooling OLS model, a one-way (individual) effect within model, and a two-way fixed-effects panel model. This multiple-model approach is designed to test both between- and within-country changes over time and their significance. The pooled OLS specifically captures the differences between all country-year observations without adding specific controls for between-country heterogeneity. The one-way fixed effects model adds examination of within-country variation over time, controlling for constant national-specific traits, while the two-way model also adds year-specific shocks affecting all countries in the sample into consideration. This approach helps research whether observed relationships are driven by differences between countries, changes over time within each state, and their combined effects.

The baseline models have the following structure:

$ECI\_Technology\_it = \beta 0 + \beta 1\ ZGII\_it + \beta 2\ Z(Ln)ManufacturingVA\_it + u\_it$

where ZGII_it is the standardized GII score, ZRD_it is standardized R&D expenditure as a share of GDP, ZHighTechExports_it is standardized high-technology exports as a share of manufactured exports, and ZLnManufacturingVA_it is the standardized logarithm of manufacturing value added.

$ECI\_Research\_it = \beta 0 + \beta 1\ GII\_it + \beta 2\ wb\_old\_age\_dependency\_pct\_working\_age + u\_it$

where GII_it is the Global Innovation Index score, RD_it is R&D expenditure as a share of GDP, and Researchers_it is the number of researchers in R&D per million people.

$ECI\_Trade\_it = \beta 0 + \beta 1\ ZGII\_it + \beta 2\ ZLnManufacturingVA\_it + \beta 3\ ZFDI\_it + u\_it$

where ZGII_it is the standardized GII score, ZLnGDPPPP_it is the standardized logarithm of GDP PPP, ZLnManufacturingVA_it is the standardized logarithm of manufacturing value added, and ZFDI_it is standardized FDI net inflows as a share of GDP.

$ECI\_Software\_it = \beta 0 + \beta 1\ GII\_it + \beta 2\ InternetUsers\_it + \beta 3\ FDI\_it + u\_it$

where GII_it is the Global Innovation Index score, InternetUsers_it is the share of internet users in the population, and FDI_it is FDI net inflows as a share of GDP. In the Technology and Trade models, selected variables are log-transformed and standardized for numerical stability, while the Research and Software models are estimated in original units.

When modeling the one-way fixed effects model, each of the ECI types adds μ_i – unobserved country-specific effects, while the two-way fixed effects adds λ_t – year-specific effects common to all countries in the sample. For inference, heteroskedasticity-robust standard errors clustered at the country level are reported for the panel models.

This separation for the baseline model ensures that the GII, as a primary variable of interest in the research, is included in the approximation of each of the ECI dimensions, while adding theoretically based variables to support the robustness of the model.

To expand the scale of investigation, an additional set of models is introduced. Similar to the baseline models, an additional step in the models replaces the GII score with matched GII pillars on a country-year basis.

The expanded model has the following structure:

*ECI_Research_it = β0 + β1.1*gii_in22_tertiary_education + β1.2*gii_in52_innovation_linkages + β2*OldAgeDependency_it + u_it*

where, in the case of ECI Research, gii_in22_tertiary_education is the Tertiary education % of population, and gii_in52_innovation_linkages is Innovation linkages SubPillar of GII.

This design eliminates some potential collinearity between independent variables and retains the most substantial parts of GII to approximate each ECI type.

Chapter 4. Results

This section reviews the results and their significance across the outlined models. The analysis proceeds from baseline regressions and then to expanded specifications using matched GII pillars and sub-pillars. The results are presented separately for each type of Economic Complexity Index, which allows for a clearer interpretation of how different dimensions of economic sophistication relate to innovation measures. The results capture a broader range of connections between innovation and complexity because the set of independent variables varies with the ECI dimension being predicted. However, since the ECI dimensions vary in terms of coverage, time span, and explanatory structure, the results should not be applied uniformly to all models. All the results bellow are reported accounting gor robustness, using the robust_se() function in R. The significance tests were performed as well to verify the validity of the further results, they are shown in the Appendix 1.

4.1 ECI TECHNOLOGY

The results for modeling ECI Technology, as well as other dimensions, are obtained by applying 3 models: a pooling OLS model, a one-way (individual) effect within model, and a two-way fixed-effects panel model. Each of these models will be reviewed and interpreted based on the results of the three models tested, and appropriate conclusions will be drawn based on the logic each modeling method applies.

Results of the ECI Technology models are represented in Table 2:

Table 2. Results of the ECI Technology models.

Variables	Pooling	Country FE	Two-way FE
GII score (z)	0.221**	0.053	0.055
	(0.070)	(0.061)	(0.093)

ln Manufacturing value added (z)	0.307***	0.008	-0.106
	(0.053)	(0.098)	(0.077)
Constant	0.827***	—	—
	(0.062)	—	—
Observations	300	300	300
Countries	28	28	28
Panel structure	Unbalanced	Unbalanced	Unbalanced
R-squared	0.6378423	0.005882938	0.01105939
Adjusted R-squared	0.6354035	-0.100892598	-0.13728170
Effects included	None	Country	Country + Year

Source: Created by the author using model results in R.

The coefficients and scores of the pooling model suggest a strong relationship between innovation-system capacities and technological complexity in the economy. In fact, a one-point increase in the GII score results, on average, in a 0.22-point increase in the ECI Technology score, holding other predictors constant (see Table 2). This suggests that a country's GII score is indeed a good indicator of its capacity for technological economic growth. Control variable Manufacturing value added is mostly positively related to technological complexity, but it te to have a negative effect when two-way fixed effects are applied. Country fixed effects and the two-way fixed effects model yield insignificant test results and quite low R-squared values. The combined results of all three models suggest that, for technological economic complexity, relationships are driven mainly by differences between countries, not by changes within the same country over time. It means that countries with higher benchmarks in GII and control variables also tend to have higher technological complexity, but the independent variables struggle to predict changes over time within the same countries.

4.2 ECI RESEARCH

Modeling this dimension of economic complexity resulted in the following table:

Table 3. Results of the ECI Research models.

Variables	**Pooling**	**Country FE**	**Two-way FE**
GII score	0.079***	-0.037***	-0.017
	(0.007)	(0.011)	(0.015)
Old-age dependency, % of working-age population	0.008	-0.022*	-0.047*
	(0.023)	(0.010)	(0.018)
Constant	-3.157***	—	—
	(0.752)	—	—
Observations	338	338	338
Countries	30	30	30

Panel structure	Unbalanced	Unbalanced	Unbalanced
R-squared	0.604	0.069	0.038
Adjusted R-squared	0.602	-0.026	-0.103
Effects included	None	Country	Country + Year

Source: Created by the author using model results in R.

Actual results reveal an interesting view on the relationship. The pooling model continues to show significant results across all predictors. But unlike in the previous type of ECI, the coefficient's actual influence is very minor. With the introduction of fixed effects, the old-age dependency ratio becomes statistically significant, but reverses its direction of influence on ECI Research (see Table 3). GII also impacts negatively in fixed effects models, losing its coefficient significance in the two-way fixed effects model. R-squared remains close to a score of 0 in fixed effect models. Results across models might suggest that the importance of innovative measures tends to diminish and even reverse its impact on research economic complexity, which can be associated with a lower role of qualitative inputs in the production of research. At the same time, old-age dependency becomes negative and statistically significant in both FE specifications, especially in the two-way FE model, indicating that aging-related demographic pressure is associated with lower research complexity within countries over time.

4.3 ECI TRADE

Results of the ECI Trade models are represented in Table 4:

Table 4. Results of the ECI Trade models.

Variables	Pooling	Country FE	Two-way FE
GII score (z)	0.281***	0.045	0.037
	(0.068)	(0.038)	(0.040)
ln Manufacturing value added (z)	0.226**	0.189	0.316
	(0.081)	(0.117)	(0.193)
FDI net inflows, % of GDP (z)	-0.003	0.008.	0.007.
	(0.018)	(0.004)	(0.004)
Constant	1.046***	—	—
	(0.062)	—	—
Observations	399	399	399
Countries	28	28	28
Panel structure	Unbalanced	Unbalanced	Unbalanced
R-squared	0.646	0.065	0.122
Adjusted R-squared	0.643	-0.012	0.015
Effects included	None	Country	Country + Year

Source: Created by the author using model results in R.

This type of economic complexity shows the most complete results. All pooling OLS model coefficients, except standardized FDI net inflows (% GDP), are statistically significant and show some positive relationship with the ECI Trade. R-squared also remains high, with diminishing scores for the fixed effects model. Logarithmized data for Manufacturing value added lost significance in both fixed-effects model (see Table 4). Such a complex sequence suggests that purchasing power parity matters more for the trade complexity of the economy when country- and year-specific factors are included, whereas GII scores are more influential when these factors are excluded. Despite that, innovative measures remain significant for all model types, but might require further detailed examination.

4.4 ECI SOFTWARE

Results of the ECI Software models are represented in Table 5:

Table 5. Results of the ECI Software models.

Variables	**Pooling**	**Country FE**	**Two-way FE**
GII score	0.059***	-0.008	-0.010
	(0.011)	(0.011)	(0.014)
Internet users, % of population	0.007	0.014.	0.001
	(0.014)	(0.008)	(0.008)

FDI net inflows, % of GDP	0.002	-0.001	-0.001.
	(0.003)	(0.0005)	(0.0003)
Constant	-2.217*	—	—
	(0.965)	—	—
Observations	[insert]	[insert]	[insert]
Countries	[insert]	[insert]	[insert]
Panel structure	Unbalanced	Unbalanced	Unbalanced
R-squared	0.620	0.164	0.015
Adjusted R-squared	0.611	-0.161	-0.417
Effects included	None	Country	Country + Year

Source: Created by the author using model results in R.

Higher innovation is correlated with more complex software, according to the pooled model, which shows a strong positive relationship between GII score and ECI software. However, when country-specific factors are taken into account, this correlation disappears in fixed-effects models, showing the GII score as small, negative, and insignificant. The only significant variable is internet use, indicating that increased internet penetration may eventually increase software complexity within nations; this finding also diminishes in the two-way FE model (see Table 5). Because of the thin and limited usable panel, which limits accurate identification, the software model generally performs worse than the trade model. Since ECI Software lacks the robustness of the data, it might be insufficient to further use in our analysis, since it is much harder to provide justification for such a weak existing link.

4.5 GII PILLARS MODELS

The extended models with detailed GII pillars appear more effective than the baseline specifications in showing which particular parts of the innovation system matter, rather than only whether the overall GII score matters. Their main value is that they make the results more concrete and much easier to translate into policy logic. At the same time, they also show that not all innovation-related dimensions are equally useful predictors of economic complexity.

The clearest result appears in the ECI Research models. Here, innovation linkages are strongly positive across all three specifications: the coefficient is 0.046 in the pooled model, 0.0003 in the country-fixed effects model, and 0.0084 in the two-way fixed effects model. This is one of the most robust findings in the analysis, as it remains significant even after controlling for both country- and year-specific effects. In practical terms, stronger cooperation between firms, universities, research institutions, and related actors is consistently associated with stronger research complexity.

For ECI Technology, the most stable detailed predictor is again innovation linkages. Its coefficient is 0.032 in the pooled model and remains positive in the two-way fixed-effects model (0.0046). ICT use is also positive in the pooled and one-way models (0.0061 and 0.0022), but loses significance in the strictest version. This means digital use matters, but its impact is less robust than that of innovation coordination itself. Controls continue to be significant only in the pool model, failing to explain links when effects are included.

The ECI Trade models highlight a different mechanism. Here, the regulatory environment is the most stable predictor: it remains positive and significant in pooled (0.03), one-way FE (0.0019), and two-way FE (0.0011) models. Investment, on the other hand, is negative in the pooled model (-0.0040) and then becomes insignificant. This suggests that investment alone does not guarantee more complex trade structures unless it is supported by better rules, institutions, and market conditions.

Overall, the empirical results suggest that the relationship between innovation and economic complexity is present but uneven. In the baseline models, much of the difference is explained by the pooled OLS model, highlighting the strength of the relationship between countries rather than by the within-country relationship. The results from expanded model types show that some pillars of innovation are more robustly connected to complexity outcomes, despite the importance of some coefficients definitely weakening.

Taken together, this suggests that policy should focus less on broad innovation expansion and more on the specific channels that repeatedly matter in the models, especially innovation linkages and regulatory quality. Thus, policies should target the institutional and coordination mechanisms that help turn knowledge, education, and infrastructure into concrete gains in economic complexity.

Chapter 5. Ukraine Analysis and Policy Implications

Compared with structurally similar European economies, Ukraine holds a mixed position. On the one hand, its complexity profile suggests a stronger productive base than its overall innovation performance alone would suggest. On the other hand, Ukraine remains weaker than several peer countries across selected innovation-system dimensions, especially those linked to coordination, knowledge diffusion, and business-side absorption. This imbalance supports the idea that productive capabilities may exist, but their translation into broader innovation outcomes remains incomplete.

To identify Ukrainian performance relative to other countries, a selection of countries was made. The broader sample includes Bulgaria, Romania, Poland, Serbia, Moldova, Hungary, Slovakia, Croatia, Turkey, Lithuania, Latvia, Estonia, and the Czech Republic. The countries in question are selected based on their similarities to Ukrainian economic performance, historical/political past (former socialist bloc), institutional factors, and geographical factors. To assess whether the countries indeed have similarities on the basis of the Economic Complexity Index, a separate comparative dataframe was created. It includes average scores for ECI Trade/Research/Technology and GII, as well as standardized z-score values for ECIs. For each country, the distance measure reflects the overall gap from Ukraine across the trade, research, and technology complexity dimensions simultaneously. Based on this estimation, countries that share the most similarities with Ukraine are Bulgaria, Romania, Poland, Serbia, Slovakia, and Lithuania.

In direct comparison with the final European peer sample, Ukraine consistently underperforms in GII scores, also having gaps in ECI Trade and ECI Research compared to other countries. From Figure 3, Ukraine's GII score is not extremely low compared to some of its peers, but its trade complexity is noticeably weaker than in most comparable economies. This suggests that Ukraine's trade structure is not disconnected from innovation, but its broader innovation performance still lags behind stronger regional comparators.

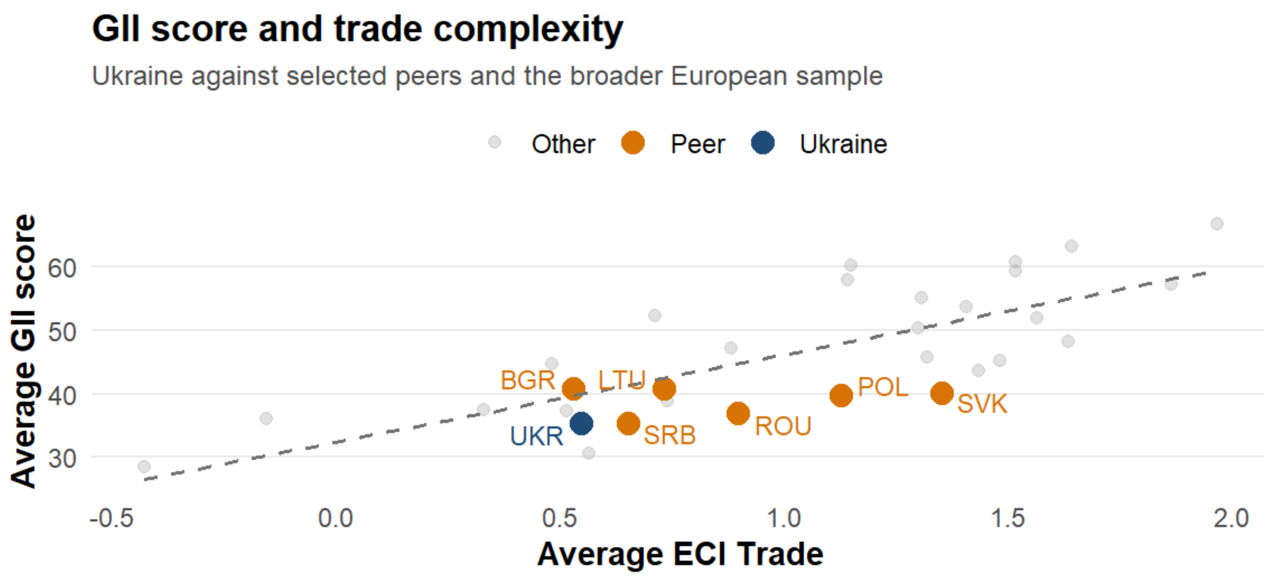

Figure 3. GII score and trade complexity; created by the authors by combination of GII and ECI Trade data.

Figure 4 suggests a similar pattern. The projected trend line closely aligns with Ukraine's performance in the GII and the complexity of its research. However, having similar scores in ECI Research Bulgaria and Lithuania, they are performing better overall in terms of innovation performance. This suggests that Ukraine`s innovative-measure scores are more aligned with the complexity of research, but it remains lower in total compared to similar European economies.

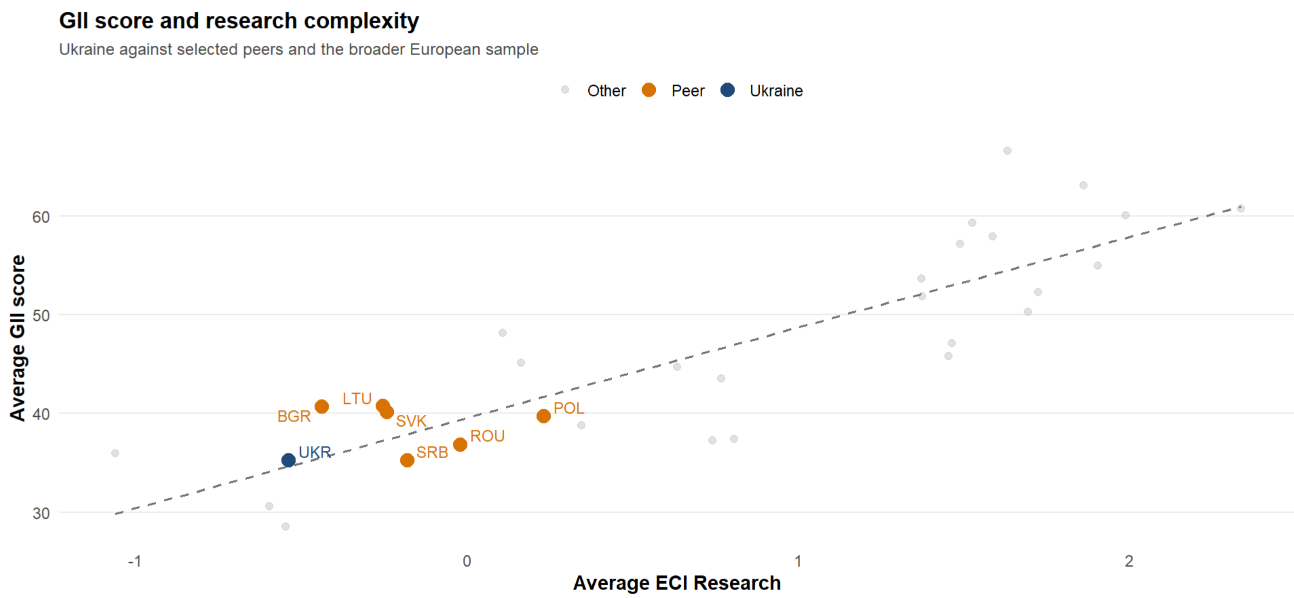

Figure 4. GII score and research complexity; created by the authors by combination of GII and ECI Research data.

Figure 5 shows a more positive picture. It shows that Ukraine has a moderate level of technology complexity, but its GII score remains below what might be expected from the broader positive relationship between innovation and technology complexity. Most selected peers, especially Poland, Slovakia, and Bulgaria, combine either stronger technology complexity or stronger innovation performance, or both. This suggests that Ukraine is not the weakest in technological structure itself, but it is weaker in the innovation conditions associated with that structure.

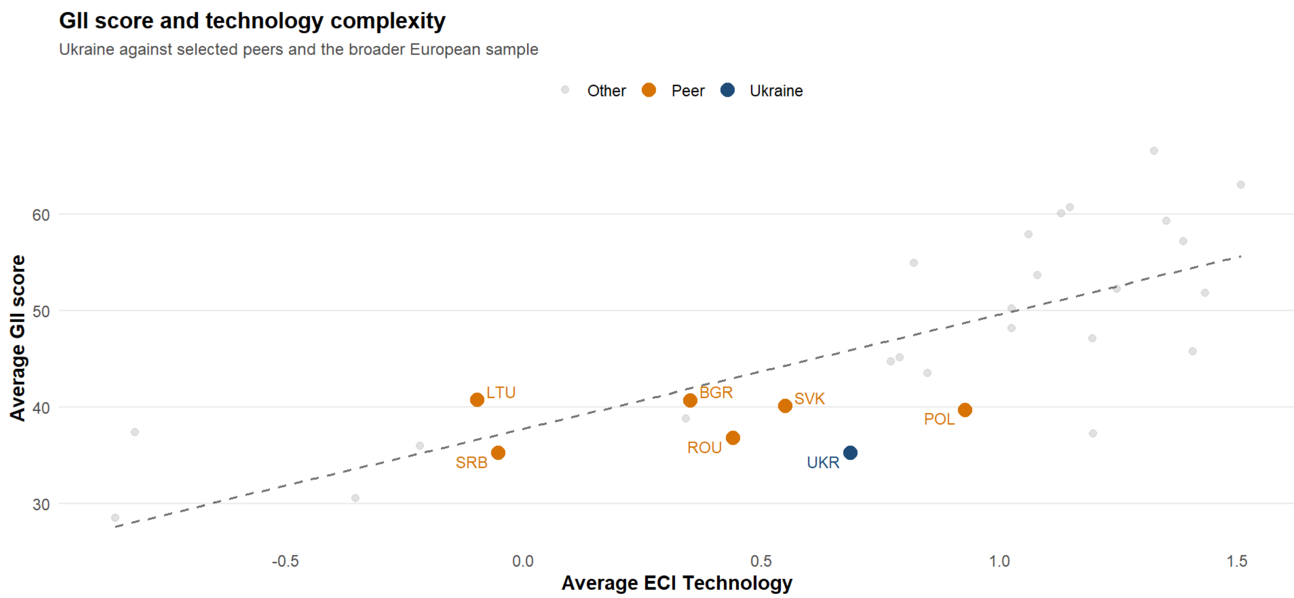

Figure 5. GII score and technology complexity; created by the authors by combination of GII and ECI Technology data.

A comparison across 3 ECI dimensions in Ukraine and similar economies in Europe shows that Ukraine is generally weaker in innovative performance, as measured by the GII, which then translates into lower economic complexity across dimensions. Yet, Ukraine's performance in terms of technology complexity shows positive signs compared with European peers.

As in the methodology section, the comparative analysis uses a deeper approach by analyzing the innovative pillars from the Global Innovation Index across the countries in the sample. This low-level comparison suggests that Ukraine not only generally underperforms in innovative and thus economic complexity, but also in key pillars that shape innovation through institutions and growth environment.

Direct comparison shows a big discrepancy between some of the pillars. Ukraine has a great gap between its European peers in ICT use, Business environment, and Regulatory environment. Gaps in other pillars are less significant, with the Tertiary education pillar 5.6 points above average (Figure 6). However, stronger pillars in this comparison appear to be the most significant. For instance, Tertiary education appears to be non-significant in the ECI Software model. Thus, it is especially important to pay attention to pillars that are way beyond average compared to other economies in the sample.

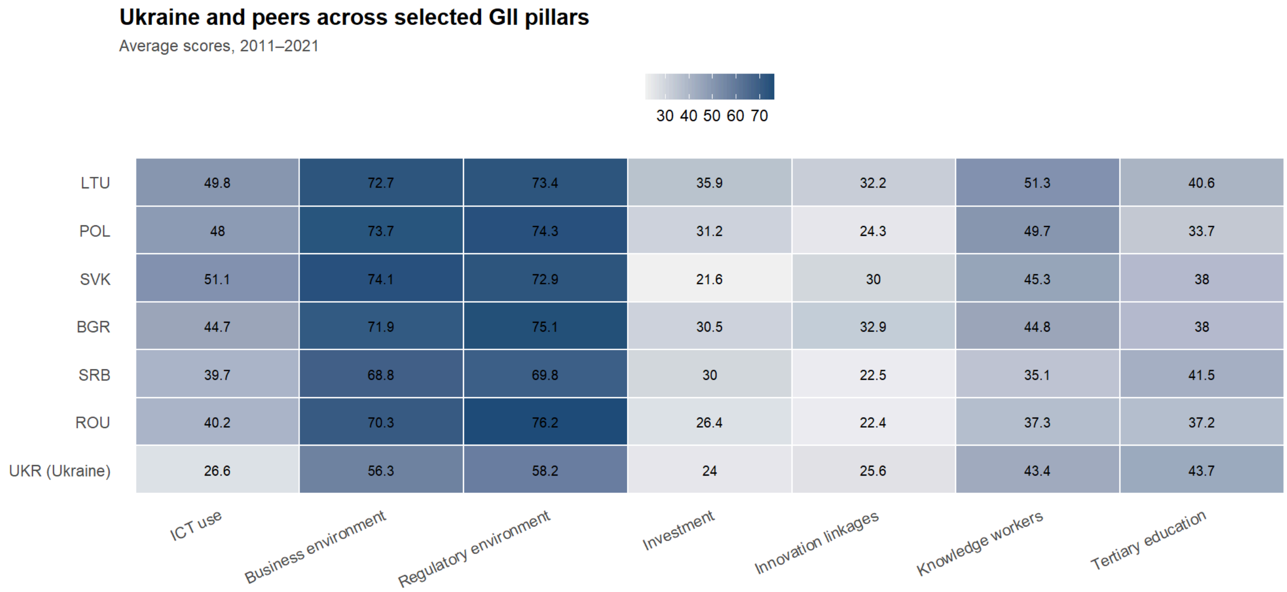

Figure 6. Ukraine and peers across selected GII pillars; created by the authors by combination of GII subpillars for selected European pears.

According to the European Innovation Scoreboard 2025, Ukraine is classified as an Emerging Innovator. Its performance is at 29% of the EU average level, and most of the rankings and performances are at lower levels compared to the EU average. The only parameter that is classified as “>125% of the EU average” is the population with tertiary education, while Exports of medium and high-tech products and Knowledge-intensive services exports are showing promising ranks and performances of 72% and 85% of the EU average, respectively. The lowest ones with the lowest place estimated are Population involved in lifelong learning, SMEs introducing product innovations, SMEs introducing business process innovations, and Sales of new-to-market and new-to-firm innovations (European Commission 4). Additionally, entrepreneurial activity in information technologies is also geographically unbalanced, leaving all the benefits of innovation to regions such as Kyiv or Lviv (Yurchyshyn 119). This might highlight an important discrepancy – despite Ukraine having the potential to have quality knowledge and exports of this knowledge, the economy struggles to convert it into long-term innovation capabilities. That innovative performance gap might be the potential driver for delaying further economic sophistication, which limits the reinvolvement of all resources into creating a more performative economic wellbeing.

More detailed data from the Ministry of Education and Science of Ukraine and Diia.City (Ministry of Digital Transformation) shows some positive dynamics. In the 2025 admission campaign, 178,720 first-year students were admitted; overall, in Ukrainian universities, there are more than 750,000 students. This number shows the positive dynamics of choosing Ukrainian universities over studying abroad, but it does not support the argument for quality education or the potential for a qualified workforce for Ukraine's economy. These statistics should also be reviewed in the broader context, since Ukraine has seen an anomalous number of male PhD (aspirants) students who are presumably avoiding mobilization, thus showing a problem with only relying on the quantity of tertiary education participants (Українська правда). Yet, some sectoral execution of knowledge seems promising. The Ministry of Digital Transformation reports that Diia.City has more than 4,000 resident companies and 148,000 IT specialists, who already form over 70% of Ukraine’s IT sector, and have paid UAH 65 billion in taxes, which is a strong domestic proxy for exportable technological and knowledge-intensive capacity (Ministry of Digital Transformation). Thus, despite wartime issues and institutional problems, Ukraine has people, niches, and sectors capable of generating more sophisticated activity.

Ministry of Education and Science of Ukraine, in its report “Scientific, Scientific-Technical, and Innovation Activities in Ukraine in 2023” specifically highlights the problems as a result of the analytical work. Those are:

- an ineffective mechanism for introducing innovations into economic activity and their subsequent commercialization;

- insufficient state support for innovative projects and their funding, both from the state budget and from private investors;
- failure to utilize all opportunities provided by the Association Agreement between Ukraine and the EU, particularly in the areas of scientific and technological cooperation, entrepreneurship development, and industrial policy;
- low level of cooperation between innovative enterprises and research institutions.

This is direct evidence that, despite promising input resources, Ukraine struggles to actually turn them into innovative performances. Furthermore, it states that direct structural changes in the economy and science should be made, “as well as modernizing production technology and encouraging businesses to innovate” (Ministry of Education and Science of Ukraine).

Research brief for the budget administrators researching the internal dynamics of innovative input capabilities. In 2024, a significant disconnect emerges between the growth in technology transfer activities and financial returns. The volume of technologies transferred increased by 24.1% to 1,519 units, yet total revenue fell by 13.91 million UAH to 95.88 million UAH, with universities transferring 306 fewer technologies and experiencing a 2.1-fold decline in revenue. While more deals are being initiated, each generates less income, indicating a decline in the commercial viability of these transactions. The technology acquisition side also reflects this trend, with spending dropping 1.8 times and agreement numbers down by 22.5%, suggesting decreased demand and investment capacity from the industry. In 2024, net revenue from product sales plummeted by 83% to 24.45 million UAH, paralleled by a similar decline in costs (Ministry of Education and Science of Ukraine). Thus, these dynamics collectively support the argument that Ukraine's formal technology transfer infrastructure operates as a distribution mechanism for scientific outputs rather than a conversion mechanism that turns research investment into economic value.

However, Ukraine not only outlines the existing innovational gap in the analytical overviews. The WINWIN 2030 strategy, adopted by the government in January 2025, explicitly prioritizes opening markets, building innovation infrastructure, deregulating innovation activity, improving access to finance, developing human capital, protecting IP, and supporting science-intensive innovation (Ministry of Digital Transformation). One of the main sectors of innovative promising capabilities is DefenseTech, MedTech, BioTech, AgroTech, AUV, semiconductors, etc. Alongside that, the Ukrainian government invested over 540 million UAH for professional education in 2025, which covers crucial tech spheres, including mechanical engineering and energy, manufacturing automation, robotics, welding and metalworking, electrical engineering and electronics (Ministry of Education and Science of Ukraine). Besides increasing efforts to increase lifelong learning, MON also increases its efforts in support of innovative activities from the early stages of development. By December 2025, Ukraine had 23 startup schools in 16 regions, six with direct state funding, supporting 150+ teams and generating 40+ prototypes (Ministry of Education and Science of Ukraine). These types of strategic activities create room for improvement and convergence with European peers. Combined with institutional and structural changes initiated by the EU and its Acquis, Ukraine has a serious potential to sustain a strong environment not only for developing innovative ideas, but also for implementing them in functioning technology and products. Efforts for more integrated links between educational institutions and businesses and continuous development for professionals are a powerful start for changing the deeply entrenched system inherited from the socialist past.

Chapter 6. Conclusions

This paper examined whether stronger innovation-system conditions are associated with higher levels of economic complexity in Ukraine and comparable European economies by combining multidimensional ECI indicators with the GII, selected pillars, and supporting controls in a panel framework. The results suggest that the relationship between innovation and complexity is real, but not uniform across all dimensions of complexity. In the baseline models, the strongest and most consistent evidence appears for ECI Trade, where GII remains positive and statistically significant across pooling, country fixed-effects, and two-way fixed-effects specifications. This indicates that innovation performance is most clearly linked to the trade-related dimension of structural sophistication. By contrast, the results for ECI Technology are driven mainly by cross-country differences rather than within-country change over time, while ECI Research produces weaker and more mixed results in the stricter specifications. The ECI Software models are the least robust because of thin coverage and should be interpreted with caution rather than treated as a central pillar of the final argument.

The extended models using GII pillars provide the clearest contribution of the study. They show that not all innovation inputs matter equally. The most stable and policy-relevant findings are concentrated in innovation linkages and regulatory quality. Innovation linkages remain positively associated with research complexity across all specifications, suggesting that cooperation between firms, universities, research institutions, and related actors is one of the most reliable channels through which innovation can be translated into more advanced productive capabilities. Regulatory environment is likewise the most stable predictor for trade complexity, implying that structural upgrading depends not only on investment or educational attainment, but also on predictable rules, institutional quality, and the business conditions under which firms operate. Taken together, these findings support the argument that economic complexity does not emerge automatically from knowledge stocks alone; it depends on the institutional and coordination mechanisms that allow knowledge to be absorbed, commercialized, and scaled.

For Ukraine, the analysis points to a clear structural imbalance. The country demonstrates a more promising productive and technological base than its aggregate innovation performance would suggest, yet it underperforms relative to comparable European peers in the very pillars that appear most important in the models. The largest gaps are concentrated in ICT use, business environment, and regulatory environment, while tertiary education performs relatively better. This means that Ukraine's main constraint is not simply a lack of human capital or sectoral potential, but a weak capacity to convert knowledge into commercially viable and complexity-enhancing outcomes. The comparison with peer countries reinforces this interpretation. It highlights that Ukraine is not devoid of capabilities, but it remains less effective at organizing, diffusing, and institutionalizing them.

The general conclusion for Ukraine is to adapt the multidimensional policy. It should not focus solely on either innovative capabilities or further sophistication, but rather the links that unite them as the paper describes. The most important ones are university-firm linkages, improvement for business and institutional regulatory conditions, expand practical diffusion channels for SMEs, and focus public support on mechanisms that help transform research, skills, and digital capacity into production and export sophistication. Thus, the paper shows that not only innovation matters for improving Ukrainian complexity, but also how the state and institutions can build the conditions under which that relationship becomes systematic rather than occasional.

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APPENDIX A

Table A1. Panel Tests Results

Model	Test	Null_hypothesis	Statistic	p_value	Conclusion
ECI Trade	F-test: Pooling vs Country FE	Pooling is sufficient; no country fixed effects	431,511	0	Reject pooling; country FE are justified
ECI Trade	LM test: Pooling vs RE	No panel effects; pooling is sufficient	1825,686	0	Reject pooling; panel effects exist
ECI Trade	Hausman test: FE vs RE	Random effects are consistent	9,339	0,0251	Reject RE; FE preferred
ECI Trade	F-test: Country FE vs Two-way FE	Country FE is sufficient; no year fixed effects	1,714	0,0563	Year effects not strongly required
ECI Technology	F-test: Pooling vs Country FE	Pooling is sufficient; no country fixed effects	51,235	0	Reject pooling; country FE are justified
ECI Technology	LM test: Pooling vs RE	No panel effects; pooling is sufficient	420,338	0	Reject pooling; panel effects exist
ECI Technology	Hausman test: FE vs RE	Random effects are consistent	6,589	0,2531	RE not rejected; FE needs theoretical justification
ECI Technology	F-test: Country FE vs Two-way FE	Country FE is sufficient; no year fixed effects	1,212	0,2984	Year effects not strongly required
ECI	F-test:	Pooling is	61,66	0	Reject

Research	Pooling vs Country FE	sufficient; no country fixed effects			pooling; country FE are justified
ECI Research	LM test: Pooling vs RE	No panel effects; pooling is sufficient	1136,34	0	Reject pooling; panel effects exist
ECI Research	Hausman test: FE vs RE	Random effects are consistent	61,694	0	Reject RE; FE preferred
ECI Research	F-test: Country FE vs Two-way FE	Country FE is sufficient; no year fixed effects	14,356	0	Year effects matter; TWFE preferred
ECI Software	F-test: Pooling vs Country FE	Pooling is sufficient; no country fixed effects	136,282	0	Reject pooling; country FE are justified
ECI Software	LM test: Pooling vs RE	No panel effects; pooling is sufficient	142,483	0	Reject pooling; panel effects exist
ECI Software	Hausman test: FE vs RE	Random effects are consistent	47,892	0	Reject RE; FE preferred
ECI Software	F-test: Country FE vs Two-way FE	Country FE is sufficient; no year fixed effects	0,371	0,7741	Year effects not strongly required

Source: Created by the author using significance tests results in R.