EXPLAINING RESEARCH AND DEVELOPMENT INVESTMENT IN THE EUROPEAN UNION: THE ROLE OF STRUCTURAL CAPACITY, ENVIRONMENTAL PRESSURES AND POLICY FRAMEWORKS

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Abstract

This study examines the structural dimensions associated with research and development investment across European Union countries through an integrated econometric framework encompassing economic performance, efficiency dynamics, environmental pressures, policy orientation, and digital transformation. Moving beyond single-indicator approaches, the analysis constructs composite indices reflecting structural innovation capacity, resource and energy efficiency, green transition pressures, fiscal and policy orientation, and digital business transformation. Using panel data for EU Member States over the period 2013–2023, the empirical strategy combines hierarchical pooled regression with country fixed-effects and two-way fixed-effects models using Driscoll-Kraay standard errors, thereby accounting for unobserved country heterogeneity, common year effects, and cross-sectional dependence. Pooled estimates show strong positive associations of structural innovation capacity and green transition pressures with BERD across variation that combines between-country differences and within-country changes. These relationships differ when estimation is based on within-country variation and when common year effects are incorporated. In the two-way fixed-effects specification with Driscoll-Kraay inference, resource and energy efficiency and green transition pressures are positively associated with BERD, whereas digital business transformation is negatively associated with BERD; structural innovation capacity and fiscal-policy orientation are not statistically significant. These results distinguish relationships

observed across pooled country-year variation from those identified through within-country changes and show that some coefficient patterns differ further after common year effects are incorporated. By providing a multidimensional perspective on the structural dimensions associated with business R&D intensity, the study contributes to the literature on sustainable innovation and provides policy-relevant evidence on the distinct roles of structural conditions, efficiency dynamics, environmental pressures, and digital transformation.

Implications for Central European audience:

For Central European economies, the findings highlight the importance of distinguishing persistent structural differences from within-country changes when evaluating business R&D investment. The positive associations of resource and energy efficiency and green transition pressures with R&D intensity suggest that industrial modernization and sustainability objectives deserve coordinated policy attention. Conversely, the negative association observed for digital business transformation under two-way fixed effects cautions against assuming that digital adoption automatically translates into higher R&D expenditure. Policymakers should therefore align digitalization, productive efficiency, and innovation support with national structural conditions while evaluating their effects through appropriate longitudinal evidence.

Keywords: Research and development investment, structural capacity, environmental pressures, resource and energy efficiency, sustainable innovation, European Union

JEL Classification: O3, M2, Q01

Introduction

The transition toward sustainable and innovation-intensive economic systems has broadened the structural context in which competitiveness and technological development evolve across the European Union. Economic performance alone provides an increasingly incomplete account of these dynamics, which are embedded in differences in innovation capacity, resource and energy efficiency, environmental transition pressures, institutional conditions, and technological readiness. Within this broader configuration, Business Enterprise Expenditure on R&D (BERD) constitutes a key macro-level expression of the resources committed by the business sector to research and technological development, linking national innovation capacity to the economic, environmental, and technological transformations confronting European economies.

At the policy level, this transition is reflected in major European strategic frameworks, including the European Green Deal (European Commission, 2023a), the Circular Economy Action Plan (European Commission, 2023b), and Horizon Europe (European Commission, 2024), which increasingly connect competitiveness, environmental sustainability, technological development, and digital transformation. Empirical research, however, has not developed these dimensions with the same degree of integration. Economic performance, energy and resource efficiency, human capital, environmental pressures, institutional conditions, and digitalization are frequently examined through separate empirical specifications, leaving comparatively less evidence on their joint configuration in relation to business R&D intensity. This fragmentation is particularly consequential in the European

context, where these dimensions evolve simultaneously and within markedly heterogeneous national innovation systems.

A related issue concerns the correspondence between conceptual framing and empirical scale (Georgescu et al., 2025; Khan et al., 2025; Majid et al., 2023; Martiny et al., 2024). Although innovation is ultimately realized through firm-level decisions, country-level indicators describe the structural environment within which those decisions occur rather than the behaviour of individual firms. The present study therefore treats BERD as a macro-level characteristic of national innovation systems and examines its association with country-level structural conditions. This distinction defines the level of inference throughout the analysis and separates structural relationships observed across national economies from firm-level behavioural mechanisms.

Against this background, the present research develops an integrated analytical framework for examining the structural dimensions associated with business R&D intensity across European Union countries. Rather than representing these dimensions through isolated indicators, the study constructs five composite indices: structural innovation capacity (SICI), resource and energy efficiency (REEI), green transition pressures (GTPI), green fiscal and policy orientation (GFPOI), and digital business transformation (DBTI). Their joint incorporation within the empirical framework permits economic, efficiency-related, environmental, policy, and digital conditions to be examined as distinct but interconnected dimensions of the structural context in which business R&D intensity evolves.

The main objective of the study is to examine how the five structural dimensions are associated with business R&D intensity and to determine how these relationships differ across complementary sources of country-year variation. This objective is operationalized through the following specific objectives:

- **O1**: To develop an integrated conceptual and empirical framework representing structural innovation capacity, resource and energy efficiency, green transition pressures, fiscal-policy orientation, and digital business transformation through composite indices.
- **O2**: To estimate the associations between these structural dimensions and BERD within a hierarchical pooled framework and to assess their incremental explanatory contribution as successive conceptual dimensions are incorporated.
- **O3**: To distinguish associations derived from combined between-country and within-country variation from those identified through within-country changes, using country fixed-effects and two-way fixed-effects specifications with robust inference.

Accordingly, the study addresses the following research question*: How are structural innovation capacity, resource and energy efficiency, green-transition pressures, fiscal-policy orientation, and digital business transformation associated with business R&D intensity across EU Member States, and how do these relationships differ between pooled country-year variation and within-country temporal variation?*

Methodologically, the study uses a balanced panel of EU Member States observed over 2013–2023 and standardizes the analytical variables to facilitate comparison across the constructed dimensions. Hierarchical pooled OLS models characterize relationships across the combined between-country and within-country variation, while country fixed-effects and

two-way fixed-effects specifications estimate within-country associations with country fixed effects and, in the two-way specification, common year effects. Driscoll-Kraay inference addresses the dependence structure identified by the panel diagnostics, and alternative index configurations examine the sensitivity of the estimates to selected compositional features of SICI and GTPI.

The contribution of the study resides in connecting multidimensional measurement with an econometric design that makes the source of empirical variation explicit. The five composite indices organize heterogeneous economic, efficiency-related, environmental, policy, and digital indicators into theoretically defined structural dimensions, while the sequential use of pooled OLS, country fixed effects, and two-way fixed effects distinguishes relationships observed across the full country-year distribution from those associated with changes occurring within countries over time. This distinction is substantively consequential: associations that appear pronounced in the pooled data do not necessarily persist under within-country identification, while other relationships become more visible after common temporal developments are accounted for. The analysis therefore shifts attention from a single ranking of structural correlates toward the conditions under which different dimensions of the innovation-sustainability environment are empirically associated with BERD.

1 Literature Review

Business research and development (R&D) investment is increasingly examined within a broader innovation-system perspective that connects firm-level research activity with the structural conditions of the economies in which firms operate. This analytical shift extends the conventional focus on individual investment decisions toward the macroeconomic and systemic configurations associated with the capacity to sustain innovation in increasingly knowledge-intensive and sustainability-oriented economies (Al Amosh, 2026; Gomes et al., 2026).

Within this broader research agenda, business R&D investment has been associated with a diverse set of structural dimensions, including economic performance, human capital, resource and energy efficiency, environmental pressures, institutional frameworks, and digital transformation (Xing et al., 2024; Yang et al., 2025). The analytical challenge lies not in establishing the relevance of these dimensions individually, but in understanding how they coexist within national innovation systems. Their continued treatment as largely separate explanatory domains limits the capacity of fragmented empirical approaches to represent the multidimensional structural setting in which business R&D activity develops.

The European Union provides a particularly relevant setting for such an integrated perspective. Substantial heterogeneity in economic development, technological capabilities, productive structures, and policy frameworks coexists with common strategic commitments to innovation, digitalization, and the green transition. Consequently, variation in business R&D intensity can be examined more informatively within a framework that accommodates several structural dimensions simultaneously rather than attributing observed differences to isolated national characteristics.

On this basis, the literature review is organized around the five dimensions subsequently represented in the empirical framework: structural innovation capacity, resource and energy efficiency, green-transition pressures, institutional and fiscal conditions, and digital

transformation. The discussion traces the theoretical mechanisms and empirical evidence associated with each dimension and establishes the conceptual basis for the corresponding research hypotheses. This structure connects the theoretical architecture of the study directly with its empirical operationalization while preserving the distinct economic meaning of the five dimensions.

1.1 Structural innovation capacity and R&D investment

Recent empirical studies (Pham et al., 2026; Q. Zhao et al., 2025) situate business research and development (R&D) investment within the broader structural characteristics of national economies, extending its interpretation beyond isolated firm-level decisions. From this perspective, economic performance and human capital form complementary dimensions of innovation capacity by defining the resource base and knowledge capabilities within which sustained R&D activity develops.

From a macroeconomic perspective, higher levels of economic development, typically proxied by GDP per capita, are consistently associated with greater private investment in innovation. The literature relates this pattern to the broader economic opportunities available in more advanced economies, including stronger and more diversified demand for innovative products and services and, consequently, more favorable expected returns to R&D activities (Cheng et al., 2026; International Monetary Fund, 2026). Higher income levels are also associated with deeper financial markets and greater access to external financing, conditions that can ease the liquidity constraints surrounding long-horizon, research-intensive investment. Institutional conditions add another dimension to this structural setting, as developed economies tend to provide more stable and predictable environments for firms committing resources to innovation (OECD, 2025d; Şengül et al., 2025).

Economic performance represents only one component of the structural environment associated with cross-country differences in R&D intensity. Human capital introduces a complementary dimension by determining the availability of the specialized knowledge and skills required within innovation systems (Awode & Oduola, 2024; Loaiza, 2026). A highly skilled workforce, particularly in science, technology, engineering, and mathematics (STEM) fields, expands firms' capacity to absorb external knowledge, develop new knowledge internally, and diffuse technological capabilities across productive activities. Empirical studies show that countries with higher concentrations of R&D personnel and knowledge-intensive workers exhibit higher levels of innovation output and investment intensity (European Union, 2024; Guzman et al., 2024).

Recent contributions extend this perspective by conceptualizing innovation capacity as a systemic and multidimensional construct rather than as a collection of isolated determinants. Economic performance, capital formation, human capital, and energy-transition dynamics represent interrelated components of the structural environment in which innovation capacity develops (Alabani et al., 2026; Bambi & Pea-Assounga, 2025). Capital accumulation, including gross fixed capital formation, represents the investment base supporting productive and research infrastructure, while renewable-energy integration introduces a transition-related dimension connected with the long-term modernization of economic systems. Considered together, these relationships provide a conceptual basis for representing innovation capacity through a multidimensional construct rather than through

individual indicators that capture only specific elements of the broader structural configuration (Saud et al., 2024; Spilioti & Anastasiou, 2024).

In the European Union, this integrated perspective is particularly relevant because persistent disparities in R&D intensity coexist with substantial differences in the structural characteristics of Member States. Economic development, capital formation, human capital, and renewable-energy integration vary considerably across national innovation systems, and countries with stronger configurations of these characteristics tend to exhibit higher levels of business R&D expenditure (Brodny & Tutak, 2024; European Commission, 2025). Their co-occurrence provides a substantive basis for examining structural innovation capacity as a broader national configuration associated with the environment in which private-sector R&D activity takes place.

Building on this theoretical and empirical foundation, the present study operationalizes structural innovation capacity through a composite-index approach. The Sustainable Innovation Capacity Index (SICI) integrates economic performance (GDP per capita), investment capacity (gross fixed capital formation), research human capital (R&D personnel), and energy transition (renewable energy share) within a common structural dimension. This construction translates the multidimensional conceptualization of innovation capacity into an empirical measure that preserves the distinct contribution of its economic, investment, human-capital, and transition-related components.

By combining these components, SICI provides an empirical representation of structural innovation capacity at the country level without reducing the construct to any single underlying indicator. The composite formulation is consistent with the theoretical premise that innovation capacity is embedded in a configuration of economic, investment, human-capital, and transition-related conditions. This conceptual correspondence between the multidimensional construct and its empirical operationalization provides the basis for the following hypothesis:

- **Hypothesis H1: Structural innovation capacity (SICI) is positively associated with business R&D intensity (BERD) at the country level.**

The hypothesis reflects the expectation that stronger configurations of economic development, capital formation, research human capital, and energy-transition conditions are associated with higher business R&D intensity. Its empirical assessment subsequently distinguishes whether this relationship is expressed primarily across the pooled country-year distribution or is also identifiable through changes occurring within countries over time.

1.2 Resource and energy efficiency and R&D investment

Energy efficiency and resource productivity are increasingly positioned in the literature as structural characteristics of the productive environment associated with innovation, particularly within the context of the green transition (Agostino et al., 2026; Dai, Mehmood, et al., 2025). Beyond their role as operational indicators, these dimensions describe the capacity of economic systems to generate value from energy and material inputs and therefore provide a broader perspective on the efficiency conditions accompanying research and innovation activity.

Specialized studies (Li & Zhou, 2026; OECD, 2025b) suggest that firms operating in environments characterized by higher levels of energy productivity are more likely to engage

in innovation, particularly in areas related to environmental sustainability and low-carbon technologies. One interpretation of this relationship emphasizes cost-efficiency mechanisms: lower energy intensity can reduce production costs and expand the internal resources potentially available for longer-horizon investment, including R&D. Higher energy productivity is also frequently associated with technologically advanced production systems in which innovation processes are more closely integrated with productive and strategic capabilities (Andrei & Johnsson, 2025; Wang et al., 2025).

Resource productivity extends the efficiency perspective to the use of materials and the organization of production processes. Within this context, eco-innovation is closely connected with firms' responses to requirements for more sustainable resource use. Several studies indicate that higher levels of resource efficiency are associated with a greater propensity to adopt eco-innovative practices, particularly in industries where material costs and environmental constraints are significant (Calvo et al., 2022; Gunarathne & Lee, 2021; Klemke-Pitek & Majchrzak, 2022; Wu & Lin, 2022). This relationship need not translate directly into higher formal R&D expenditure, since efficiency-oriented adjustments may also take the form of process optimization, waste reduction, or supply-chain reorganization.

The empirical literature therefore provides a heterogeneous account of the relationship between resource efficiency and R&D intensity. In some settings, higher resource productivity coincides with stronger innovation activity and with productive conditions favorable to technological adjustment. In others, the relationship becomes visible only over longer horizons, consistent with the gradual structural changes associated with circular-economy transitions. Differences in sectoral composition, technological maturity, and institutional context provide additional explanations for this variation across countries (Premkumar et al., 2025; Prokop et al., 2023; Usman et al., 2022).

From a systemic perspective, energy and resource efficiency can be interpreted as structural conditions associated with the productive context in which innovation occurs (Faerber et al., 2026; World Economic Forum, 2025). Their relevance differs conceptually from that of economic development or human capital because efficiency indicators describe how effectively productive systems transform energy, materials, and labor into economic value. The relationship with R&D may consequently operate through several channels, including production modernization, resource allocation, technological upgrading, and the reorganization of existing processes, making efficiency a distinct component of the broader structural environment surrounding innovation.

In the European Union, this relationship is particularly relevant because energy and resource efficiency vary substantially across Member States. Differences in these dimensions reflect heterogeneous trajectories of industrial modernization and environmental policy implementation (Coelho et al., 2025; Kumar et al., 2025). Their coexistence with marked differences in technological capacity, productive structure, and business R&D intensity makes the EU setting particularly suitable for examining whether efficiency-related conditions are associated with innovation not only across countries but also through changes occurring within national economies over time.

To represent this multidimensional and context-dependent relationship empirically, the present study constructs the Resource and Energy Efficiency Index (REEI), which integrates energy productivity, resource productivity, and labor productivity into a composite measure.

The index provides a common representation of productive efficiency at the macroeconomic level while retaining the conceptual contribution of the three underlying dimensions.

Taken together, the literature provides a theoretical basis for expecting a positive relationship between productive efficiency and innovation while also indicating that its empirical expression may vary across structural and temporal contexts. The corresponding hypothesis is formulated as follows:

- **Hypothesis H2: Resource and energy efficiency (REEI) is positively associated with business R&D intensity (BERD).**

The hypothesis reflects the expectation that higher levels of resource, energy, and labor productivity are associated with higher business R&D intensity. Given the heterogeneous relationships identified in the literature, the empirical analysis subsequently examines whether this association is observed across the pooled country-year structure and whether it persists when estimation is based on within-country variation.

1.3 Environmental pressures and transition dynamics

The transition toward a low-carbon economy places environmental conditions in an increasingly prominent position within the innovation environment faced by firms and national economies. The literature describes a dual relationship in which environmental pressures can impose adjustment constraints while also increasing the relevance of technological adaptation and innovation (Pan et al., 2025; Zheng et al., 2025). Greenhouse gas emissions, energy consumption patterns, and waste generation can therefore be interpreted not only as environmental outcomes of economic activity, but also as characteristics of the structural context within which technological and investment decisions evolve.

A growing stream of literature suggests that environmental pressures can stimulate innovation by increasing the cost of non-compliance and technological inertia (Dai, Phan Ah Kiaw, et al., 2025; Oyelakin et al., 2025). Within this perspective, stricter environmental constraints can alter the relative attractiveness of cleaner production processes, energy-efficient technologies, and products aligned with sustainability requirements. This reasoning is consistent with the logic of induced innovation, which identifies regulatory and environmental constraints as potential sources of technological adaptation and increased research activity (Coca et al., 2026; Fragkos et al., 2026).

The relationship between environmental pressures and innovation is not necessarily unidirectional. The literature also identifies short-term economic burdens associated with environmental adjustment, particularly in industries characterized by high energy intensity or limited technological flexibility (Ge & Zhang, 2025; Luo et al., 2025). Compliance costs, the reallocation of capital toward environmental upgrading, and uncertainty surrounding regulatory change may compete with R&D for financial and organizational resources. The resulting tension between adjustment costs and technological adaptation helps account for heterogeneous empirical relationships and indicates that the association between environmental pressures and innovation is embedded in broader structural and institutional conditions.

The European Union provides a particularly relevant setting for examining these dynamics because environmental transition objectives are embedded in a common policy framework while productive and technological conditions remain heterogeneous across Member States. The European Green Deal (European Commission, 2023a) places climate neutrality, emissions reduction, and sustainable economic transformation within the EU strategic framework. Against this policy background, regulatory requirements, carbon-reduction commitments, and sustainability objectives form part of the environment in which firms and national innovation systems adjust their technological and investment strategies.

The temporal dimension further complicates this relationship. Countries characterized by higher levels of environmental pressure may also develop regulatory frameworks and innovation ecosystems oriented toward the transition to more sustainable production models (Khalique et al., 2025; Pariso & Marino, 2026). Environmental pressure can therefore coexist with institutional and technological changes unfolding over different time horizons, making it analytically important to distinguish persistent cross-country configurations from changes observed within countries over time.

From an analytical perspective, this multidimensional environmental context requires a representation that extends beyond any single pressure indicator. The present study operationalizes this dimension through the Green Transition Pressure Index (GTPI), which combines greenhouse gas emissions, primary energy consumption, municipal waste generation, and the inverse contribution of the renewable-energy share. The index therefore represents the broader configuration of environmental and energy pressures associated with the green transition rather than a single regulatory or environmental mechanism.

This composite approach permits the relationship between the broader green-transition environment and business R&D intensity to be examined at the macroeconomic level while retaining the multidimensional character of the underlying environmental and energy conditions. The theoretical arguments concerning technological adaptation provide the basis for the following hypothesis:

- **Hypothesis H3: Green transition pressure (GTPI) is positively associated with business R&D intensity (BERD).**

The hypothesis reflects the expectation, derived from the induced-innovation perspective, that stronger green-transition pressure is associated with higher business R&D intensity. At the same time, the competing adjustment mechanisms identified in the literature make the empirical expression of this relationship an open question across pooled country-year and within-country variation.

1.4 Institutional and fiscal environment

Institutional quality and public policy frameworks constitute important dimensions of national innovation systems and define part of the regulatory and economic environment surrounding firms' research and development activities (Casadella & Tahi, 2025; Singh et al., 2024). Within this context, regulatory clarity, fiscal instruments, and government support mechanisms establish conditions that can alter the incentives, resources, and constraints associated with private investment in innovation.

The literature associates well-designed institutional frameworks with lower uncertainty and greater predictability in the business environment, conditions that can support longer-term commitments to R&D (Agostino et al., 2026; OECD, 2026a). Fiscal incentives, including tax credits, subsidies, and targeted public investments, are commonly employed to reduce the effective cost of innovation and share some of the financial risks associated with research activities. Empirical studies report positive relationships between such mechanisms and firms' innovation behavior, particularly in sectors characterized by high technological intensity and uncertain returns to research investment (Fan & Shi, 2025; Yoshino et al., 2023).

The relationship between institutional and fiscal interventions and innovation is not uniform across economic settings. A growing body of research emphasizes that policy outcomes are context-dependent, varying with the structural characteristics of national economies, governance quality, and the degree of alignment between policy objectives and market conditions (Barra & Falcone, 2025; Karagkouni & Dimitriou, 2025). Differences in innovation capacity, administrative effectiveness, technological readiness, and absorptive capacity can consequently accompany substantial variation in the way comparable policy instruments are translated into innovation activity across countries. Related firm-level evidence connects sustainability practices with financial performance and market valuation, although these outcomes are distinct from R&D intensity (Suharman et al., 2026).

Empirical research further connects the institutional and policy environment with private research activity. Clearer regulatory frameworks, fiscal incentives, and government support mechanisms have been associated with higher levels of private R&D investment, although the observed relationships vary across institutional and economic settings (Chahdoura et al., 2026; Petković et al., 2025).

The literature also indicates that relationships between policy interventions and R&D investment may unfold through indirect channels and over extended time horizons (Crucitti et al., 2025; Fu, 2026). Fiscal and regulatory measures can operate through the broader innovation environment, including infrastructure, knowledge networks, and collaboration between public and private actors, rather than being reflected immediately in private research expenditure. Their correspondence with R&D intensity may therefore depend on complementary structural conditions such as human capital, technological readiness, and market development.

Within the European Union, this heterogeneity is particularly relevant. EU-level strategies and funding programs establish common objectives for innovation and the green and digital transitions, while national implementation, administrative capacity, and institutional quality differ substantially across EU Member States (OECD, 2025a; Tiganasu & Lupu, 2023). These differences place the relationship between policy orientation and business R&D within broader national structural and institutional configurations rather than within a uniform European policy environment. Evidence on the allocation of EU structural and investment funds further illustrates the relationship between European financing instruments and green-transition performance (Bigerna et al., 2025).

To operationalize the fiscal-policy dimension at the macroeconomic level, the present study constructs the Green Fiscal and Policy Orientation Index (GFPOI), which reflects the extent to which fiscal resources and public investment are oriented toward environmental objectives. By combining environmental taxation and climate-related public investment, the index

provides a composite representation of the green orientation of fiscal and public-investment policy rather than a direct measure of firm-level innovation support or institutional quality.

This composite formulation allows the macro-level relationship between green fiscal-policy orientation and business R&D intensity to be examined as a distinct dimension of the broader innovation environment. The theoretical and empirical relationships identified in the literature provide the basis for the following hypothesis:

- **Hypothesis H4: Green fiscal and policy orientation (GFPOI) is positively associated with business R&D intensity (BERD).**

The hypothesis reflects the expectation that a stronger green orientation of fiscal and public-investment policy is associated with higher business R&D intensity. Given the cross-country heterogeneity emphasized in the literature, the empirical analysis subsequently examines how this relationship appears in the pooled country-year structure and whether it is also observed through within-country variation over time.

1.5 Digital transformation and business innovation

Digital transformation has become an increasingly relevant component of the technological environment in which firms generate, process, and exchange knowledge. Within the innovation literature, digitalization is conceptualized as an enabling infrastructure associated with the development of new business models, greater operational efficiency, and the diffusion of technological capabilities across sectors (Hönigsberg et al., 2026; Nichifor et al., 2026).

From a firm-level perspective, technologies such as cloud computing, big data analytics, and digital platforms expand the technological infrastructure available for information processing, communication, and coordination within and across organizations. These capabilities can support more flexible innovation processes and facilitate organizational responses to changing market and technological conditions. Empirical studies indicate that firms operating in digitally advanced environments exhibit a higher propensity to engage in research and development activities, particularly in knowledge-intensive industries where data-driven innovation plays a substantial role (Heras-Rosas et al., 2026; López-Paredes et al., 2025).

The relationship between digitalization and R&D investment is embedded in broader structural conditions. Digital transformation interacts with existing innovation capacities through the organization, creation, and utilization of knowledge (Duan et al., 2024; Saeedikiya et al., 2025). Economies characterized by strong human capital, advanced infrastructure, and higher levels of economic development may be better positioned to integrate digital technologies into innovation activity (Fedajev et al., 2025; Vărzaru & Bocean, 2024). Differences in skills, infrastructure, technological capabilities, and institutional readiness can therefore accompany substantial variation in the relationship between digitalization and R&D across economic settings.

Digitalization is also closely connected with other dimensions of innovation systems. Digital tools can facilitate knowledge exchange, contribute to process optimization, and improve information flows and coordination across organizational and institutional settings (Jiao et al., 2025; Xiong et al., 2025). These connections place digital transformation within a broader configuration of human capital, productive efficiency, technological infrastructure, and

institutional conditions, making its relationship with R&D inherently interconnected with other characteristics of national innovation systems.

In the European Union, digital transformation represents a strategic priority, supported by initiatives aimed at improving connectivity, fostering digital skills, and promoting the adoption of digital technologies by businesses (OECD, 2025c, 2026b). At the same time, substantial disparities persist across Member States in digital infrastructure, technology adoption, and the integration of digital technologies into economic activity (Košíková & Vašaničová, 2025). This heterogeneity provides a substantive basis for examining digital business transformation as a distinct structural dimension whose relationship with R&D intensity may differ across national settings and over time.

To operationalize the digital dimension of the business environment, the present study constructs the Digital Business Transformation Index (DBTI), which combines indicators of enterprise digitalization, online activity, and connectivity. The composite index provides a macro-level representation of the extent to which business activity takes place within digitally integrated markets and technological infrastructures.

This composite formulation allows digital business transformation to be examined as a distinct structural dimension within the multidimensional empirical framework. The positive relationships between digital capability and innovation activity identified in the literature provide the basis for the following hypothesis:

- **Hypothesis H5: Digital business transformation (DBTI) is positively associated with business R&D intensity (BERD).**

The hypothesis reflects the expectation that greater digital integration of the business environment is associated with higher business R&D intensity. Given the structural interdependencies identified in the literature, the empirical analysis subsequently examines how this relationship differs between the combined country-year variation represented by pooled estimation and the within-country variation identified by the panel specifications.

1.6 Research gap and contribution

The literature reviewed above demonstrates substantial interest in the economic, efficiency-related, environmental, institutional, and digital conditions associated with business research and development (R&D) investment. These dimensions, however, are frequently examined through separate empirical perspectives, with individual studies emphasizing particular components of national innovation systems. Consequently, comparatively less attention has been devoted to their simultaneous representation within a common macro-level framework capable of preserving their distinct conceptual meanings.

A related gap concerns the correspondence between the multidimensional conceptualization of innovation systems and their empirical operationalization. Economic capacity, productive efficiency, environmental transition pressures, policy orientation, and digital transformation describe conceptually different aspects of the environment surrounding business R&D, yet their empirical representation through numerous individual indicators can obscure the structural dimensions to which those indicators belong. Organizing related indicators into theoretically defined composite dimensions offers an alternative way of examining these characteristics jointly while maintaining their conceptual differentiation.

The reviewed evidence also indicates that the empirical relationships between these structural dimensions and R&D intensity are not uniform across economic settings. Differences in sectoral composition, technological capacity, institutional conditions, and stages of economic and environmental transition can accompany substantial variation in estimated relationships. This heterogeneity makes it important to examine the dimensions within a common empirical framework without imposing an a priori hierarchy regarding their relative contribution to business R&D intensity.

An additional empirical issue concerns the source of variation underlying the estimated relationships. Associations observed across pooled country-year data can reflect both persistent differences between countries and changes occurring within countries over time, whereas fixed-effects specifications identify relationships from within-country variation after time-invariant country characteristics are removed. Distinguishing these sources of variation is particularly relevant in the European Union, where substantial structural heterogeneity coexists with common economic, technological, and policy developments across Member States.

Against this background, the study develops a multidimensional analytical framework organized around five composite indices representing structural innovation capacity (SICI), resource and energy efficiency (REEI), green transition pressure (GTPI), green fiscal and policy orientation (GFPOI), and digital business transformation (DBTI). The framework brings economic capacity, investment, research human capital, energy and resource efficiency, environmental pressures, fiscal-policy orientation, and business digitalization into a common empirical structure while preserving their organization into conceptually distinct dimensions.

The econometric contribution lies in examining these dimensions through complementary sources of variation. Hierarchical pooled regression evaluates their incremental explanatory contribution across the combined country-year distribution, while country fixed effects identify associations from changes occurring within countries after time-invariant national characteristics are removed. The two-way fixed-effects specification additionally controls for common year-specific developments across EU Member States, allowing the within-country relationships to be examined net of shocks and temporal conditions shared across the panel.

This design makes the distinction between structural cross-country patterns and within-country dynamics an explicit component of the empirical analysis rather than treating coefficients obtained from different estimators as directly interchangeable. It also permits the sensitivity of the estimated relationships to common year effects and alternative composite-index configurations to be evaluated within the same analytical framework. The empirical contribution therefore lies not in assigning a fixed hierarchy to the five structural dimensions, but in establishing how their relationships with BERD differ according to the source of variation and the econometric specification through which they are identified.

Taken together, these elements position the study at the intersection of innovation economics, sustainability transition research, and comparative panel analysis. Its contribution derives from combining multidimensional measurement with an econometric design that distinguishes pooled country-year relationships from within-country dynamics and from within-country relationships estimated after common temporal developments are taken into account. This structure provides the conceptual and empirical basis for examining business

R&D intensity as a macro-level characteristic embedded in heterogeneous national innovation systems.

2 Methodology

This section presents the data structure, variable and composite-index construction, econometric specifications, diagnostic procedures, and sensitivity analysis used to examine the structural dimensions associated with business R&D intensity across European Union Member States.

2.1 Data structure, variables, and composite-index construction

The empirical analysis uses a balanced panel comprising the 27 European Union Member States observed annually over 2013–2023, yielding 297 country-year observations. The variables are drawn from harmonized Eurostat datasets and cover economic performance, investment, research human capital, energy and resource efficiency, environmental conditions, fiscal-policy orientation, and business digitalization (Table 1). The use of a common statistical framework provides a consistent basis for constructing the country-year panel across the indicators included in the analysis.

Table 1 | Variables included in the empirical analysis and composite-index construction

No.	Variable symbol	Variable name	Construction* / Components	Unit	Code (Source)
1	BERD	Business enterprise expenditure on R&D (dependent variable)	-	Euro per inhabitant	*rd_e_berdindr2__custom_17316464* (Eurostat, 2026a)
2	GDP	Real GDP per capita	SICI	Euro per inhabitant	*tipsna40* (Eurostat, 2026k)
3	GFCF	Gross fixed capital formation	SICI	% of GDP	*tec00011* (Eurostat, 2026e)
4	RDPERS	R&D personnel	SICI	% of labour force (FTE)	*sdg_09_30* (Eurostat, 2026j)
5	SRNWEN	Share of renewable energy	+SICI -GTPI	%	*sdg_07_40* (Eurostat, 2026l)
6	GHGE	Greenhouse gas emissions	GTPI	Thousand tonnes	*env_air_gge* (Eurostat, 2025b)
7	MWASTE	Municipal waste	GTPI	Kg per capita	*cei_pc031* (Eurostat, 2026h)
8	PEC	Primary energy consumption	GTPI	Mtoe	*sdg_07_10* (Eurostat, 2026i)
9	ENGPROD	Energy productivity	REEI	Euro per KGOE	*sdg_07_30* (Eurostat, 2026c)
10	RESPROD	Resource productivity	REEI	Euro per kg	*cei_pc030* (Eurostat, 2025d)
11	LBPRDCT	Labour productivity	REEI	Index (2015 = 100)	*nama_10_lp_ulc* (Eurostat, 2026g)
12	ENVTXREV	Environmental tax revenues	GFPOI	% of total taxes	*env_ac_tax* (Eurostat, 2026d)

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No.	Variable symbol	Variable name	Construction* / Components	Unit	Code (Source)
13	INVCLCH	Climate change mitigation investments	GFPOI	% of GDP	*env_ac_ccminv* (Eurostat, 2025c)
14	ECOMSALE	E-commerce sales	DBTI	% of turnover	*isoc_ec_evaln2* (Eurostat, 2026m)
15	ENTRINTAC	Enterprise internet access	DBTI	% of enterprises	*isoc_ci_in_es* (Eurostat, 2026f)
16	ENTRORDONLINE	Enterprises receiving online orders	DBTI	% of enterprises	*tin00111* (Eurostat, 2026b)
17	BDINTCOV	Broadband internet coverage	DBTI	% of households	*isoc_cbs* (Eurostat, 2025a)

Note: * Composite indices are constructed from standardized (*Z-score*) components so that indicators expressed in different measurement units enter the aggregation on a common scale.
Source: Eurostat

The dependent variable is Business Enterprise Expenditure on R&D (BERD), expressed in euro per inhabitant. At the country level, BERD represents the intensity of R&D expenditure undertaken by the business enterprise sector and is treated in this study as a macro-level characteristic of the national innovation system. It is not interpreted as a direct measure of sustainability-oriented investment or of individual firms' innovation behaviour. Accordingly, the empirical analysis examines country-level associations between BERD and the structural dimensions represented by the explanatory variables and composite indices.

The explanatory variables comprise economic, environmental, efficiency-related, fiscal, and digital indicators selected according to the conceptual dimensions developed in the literature review (Table 1). Rather than entering all underlying indicators separately into the econometric specifications, conceptually related variables are organized into five theory-defined composite indices. This construction provides an empirical representation of the multidimensional framework while retaining the substantive distinction among structural innovation capacity, resource and energy efficiency, green-transition pressure, fiscal-policy orientation, and digital business transformation.

Prior to aggregation, the variables entering the composite indices are standardized using Z-scores so that indicators expressed in different measurement units contribute to index construction on a common scale:

$$Z(X_{it}) = \frac{X_{it} - \mu_X}{\sigma_X} \tag{1}$$

where μ_X and σ_X denote the mean and standard deviation of variable X, respectively.

Means and standard deviations are calculated over the full country-year sample used in the analysis.

Based on the standardized variables, five composite indices are constructed to capture distinct structural dimensions.

The Sustainable Innovation Capacity Index (SICI) is defined as:

$$SICI_{it} = \frac{Z(GDP_{it}) + Z(GFCF_{it}) + Z(RDPERS_{it}) + Z(SRNWEN_{it})}{4} \quad (2)$$

where: i denotes the country index, and $t$denotes the time period (year); $Z(\cdot)$represents the standardized value (Z-score) of each variable (see Table 1).

SICI represents structural innovation capacity through four components: economic development, investment intensity, research human capital, and renewable-energy integration. Higher index values correspond to country-year observations characterized by higher standardized values across this combination of structural conditions.

The Green Transition Pressure Index (GTPI) is defined as:

$$GTPI_{it} = \frac{Z(GHGE_{it}) + Z(MWASTE_{it}) + Z(PEC_{it}) - Z(SRNWEN_{it})}{4} \quad (3)$$

where: i denotes the country index, and $t$denotes the time period (year); $Z(\cdot)$represents the standardized value (Z-score) of each variable (see Table 1).

GTPI represents environmental and energy-related transition pressure through greenhouse gas emissions, primary energy consumption, municipal waste generation, and the renewable-energy share entered with a negative sign. The reverse coding of the renewable-energy component means that higher renewable-energy shares reduce the value of GTPI, whereas higher values of the other components increase it. Higher GTPI values therefore represent stronger environmental and energy pressure within the index construction.

The Resource and Energy Efficiency Index (REEI) is defined as:

$$REEI_{it} = \frac{Z(ENGPROD_{it}) + Z(RESPROD_{it}) + Z(LBPRDCT_{it})}{3} \quad (4)$$

where: i denotes the country index, and $t$denotes the time period (year); $Z(\cdot)$represents the standardized value (Z-score) of each variable (see Table 1).

REEI represents productive efficiency through energy productivity, resource productivity, and labour productivity. Higher values indicate country-year observations characterized by higher standardized productivity across these three components.

The Green Fiscal and Policy Orientation Index (GFPOI) is defined as:

$$GFPOI_{it} = \frac{Z(ENVTXREV_{it}) + Z(INVCLCH_{it})}{2} \quad (5)$$

where: i denotes the country index, and $t$denotes the time period (year); $Z(\cdot)$represents the standardized value (Z-score) of each variable (see Table 1).

GFPOI represents the green orientation of fiscal and public-investment policy by combining environmental tax revenues and climate-change mitigation investment. Higher values correspond to a stronger joint representation of these two policy-related components within the country-year observation.

Finally, the Digital Business Transformation Index (DBTI) is defined as:

$$DBTI_{it} = \frac{Z(ECOMSALE_{it}) + Z(ENTRINTAC_{it}) + Z(ENTRORDONLINE_{it}) + Z(BDINTCOV_{it})}{4} \quad (6)$$

where: i denotes the country index, and $t$denotes the time period (year); $Z(\cdot)$represents the standardized value (Z-score) of each variable (see Table 1).

DBTI represents business digitalization through e-commerce sales, enterprise internet access, enterprises receiving online orders, and broadband internet coverage. Higher values indicate a greater standardized presence of these digital characteristics within the business and connectivity environment.

All five composite indices are calculated as equal-weight averages of their standardized components; no empirical weighting procedure is used. Within SICI, R&D personnel (RDPERS) represents the research human-capital component alongside GDP per capita, gross fixed capital formation, and the renewable-energy share. GTPI combines greenhouse gas emissions and primary energy consumption measured in absolute terms with municipal waste measured per capita and the negatively coded renewable-energy share. Consequently, GTPI incorporates both scale-related and intensity-related environmental information rather than representing a size-neutral measure of environmental pressure. The renewable-energy share (SRNWEN) enters SICI positively and GTPI negatively because it performs different conceptual roles in the two constructs: renewable-energy integration within structural innovation capacity and inverse transition pressure within GTPI. These compositional features are examined explicitly through alternative index configurations in the sensitivity analysis described in Section 3.3.

The composite indices allow the empirical specification to represent broader theoretically defined dimensions rather than entering all underlying indicators individually. Each index constitutes an analytical representation of its corresponding structural dimension, and its estimated coefficient is interpreted as the macro-level association between that composite dimension and standardized business R&D intensity.

The resulting analytical dataset combines standardized BERD with the five composite indices and forms the basis for the econometric specifications presented in Section 2.2.

2.2 Model specification

The empirical analysis uses a multiple linear regression framework to examine the associations between standardized business R&D expenditure and the five structural dimensions represented by the composite indices. BERD is standardized as a Z-score, while the composite predictors are constructed from standardized components, placing the variables used in the regression framework on comparable standardized scales.

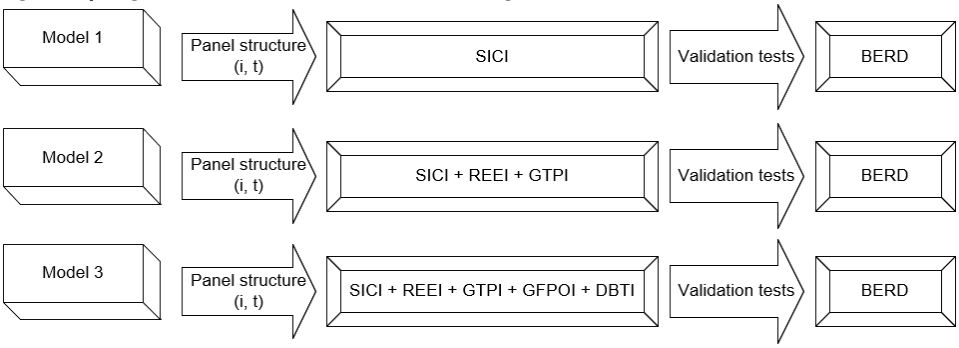
The general econometric specification is expressed as follows:

$$ZBERD_{it} = \alpha + \beta_1 SICI_{it} + \beta_2 REEI_{it} + \beta_3 GTPI_{it} + \beta_4 GFPOI_{it} + \beta_5 DBTI_{it} + \varepsilon_{it} \quad (7)$$

where *i* indexes countries, *t* indexes years, the intercept is represented by the constant term, the β coefficients correspond to the five composite predictors, and the error term captures the unexplained country-year variation in standardized BERD.

The pooled specification is estimated hierarchically by introducing the five composite dimensions in successive conceptual blocks corresponding to the analytical framework (Figure 1).

Figure 1 | Logical structure of the hierarchical regression models



The hierarchical sequence is used to assess changes in explained variation as successive structural dimensions are incorporated into the pooled specification.

Model 1 includes the Sustainable Innovation Capacity Index (SICI) as the sole composite predictor:

$$ZBERD_{it} = \alpha + \beta_1 SICI_{it} + \varepsilon_{it} \quad (8)$$

Model 1 provides the initial pooled specification for the association between structural innovation capacity and BERD, with SICI representing economic development, investment intensity, research human capital, and renewable-energy integration.

Model 2 extends the pooled specification by adding the Resource and Energy Efficiency Index (REEI) and the Green Transition Pressure Index (GTPI):

$$ZBERD_{it} = \alpha + \beta_1 SICI_{it} + \beta_2 REEI_{it} + \beta_3 GTPI_{it} + \varepsilon_{it} \quad (9)$$

This specification introduces productive-efficiency and green-transition dimensions alongside structural innovation capacity and permits their additional contribution to the explained pooled variation in BERD to be assessed.

Model 3 completes the pooled specification by adding the Green Fiscal and Policy Orientation Index (GFPOI) and the Digital Business Transformation Index (DBTI):

$$ZBERD_{it} = \alpha + \beta_1 SICI_{it} + \beta_2 REEI_{it} + \beta_3 GTPI_{it} + \beta_4 GFPOI_{it} + \beta_5 DBTI_{it} + \varepsilon_{it} \quad (10)$$

The change in R^2 between Models 2 and 3 quantifies the additional pooled variation in BERD explained when the fiscal-policy and digital dimensions are incorporated into the hierarchical specification.

The hierarchical models are initially estimated using pooled Ordinary Least Squares (OLS), with statistical significance assessed at conventional levels. Because pooled OLS uses the full country-year variation in the panel, its coefficients reflect a combination of between-country differences and within-country changes over time and are therefore not interpreted as pure cross-country associations. Within this framework, the hierarchical sequence is used to assess changes in explained variation as successive conceptual blocks are incorporated.

A country fixed-effects specification is subsequently estimated to control for unobserved time-invariant heterogeneity across EU Member States. Unlike pooled OLS, the country fixed-effects estimator identifies the coefficients from changes occurring within countries over time after time-invariant country-specific characteristics are removed. The resulting estimates are therefore interpreted as within-country associations between changes in the composite dimensions and changes in standardized BERD.

$$ZBERD_{it} = \alpha_i + \beta_1 SICI_{it} + \beta_2 REEI_{it} + \beta_3 GTPI_{it} + \beta_4 GFPOI_{it} + \beta_5 DBTI_{it} + u_{it} \quad (11)$$

were: α_i represents the fixed effect for indexes country *i*, *t* indexes years, and the idiosyncratic error term represents the remaining country-year variation.

The country fixed-effects specification is subsequently extended to a two-way fixed-effects (TWFE) model that includes both country and year effects:

$$ZBERD_{it} = \beta_1 SICI_{it} + \beta_2 REEI_{it} + \beta_3 GTPI_{it} + \beta_4 GFPOI_{it} + \beta_5 DBTI_{it} + \alpha_i + \lambda_t + \varepsilon_{it}, \quad (12)$$

where α_i represent country fixed effects and λ_t represent year fixed effects. The year effects absorb common temporal developments affecting the EU sample in a given year, so that the coefficients are estimated from within-country variation after accounting for both time-invariant country characteristics and common year-specific variation. This distinction is relevant over 2013–2023, a period that includes common economic, energy-market, technological, and pandemic-related developments across EU Member States.

The hierarchical pooled models assess the incremental contribution of successive conceptual blocks while retaining both between-country and within-country variation. The country fixed-effects specification estimates the relationships from within-country variation after controlling for time-invariant country heterogeneity, whereas the TWFE specification additionally absorbs common year-specific variation. The three specifications are therefore interpreted as complementary rather than interchangeable because they differ in the variation used to estimate the coefficients and in the unobserved heterogeneity accounted for by the model.

2.3 Econometric strategy, diagnostics and robustness checks

The econometric strategy combines panel-data estimation, diagnostic testing, robust covariance inference, and composite-index sensitivity analysis to account for relevant features of the panel structure, including unobserved country heterogeneity, heteroskedasticity, cross-sectional dependence, and potential serial correlation.

Given the balanced panel structure of the dataset (27 countries observed annually over 2013–2023, *N* = 297), the empirical strategy distinguishes among three complementary specifications. Hierarchical pooled OLS evaluates incremental explanatory power while retaining both between-country and within-country variation. Country fixed effects estimate the relationships from within-country variation after accounting for time-invariant country heterogeneity, whereas the two-way fixed-effects specification additionally incorporates year effects to account for common year-specific variation. Driscoll-Kraay standard errors are used for robust inference in the fixed-effects specifications in response to the heteroskedasticity and cross-sectional dependence identified by the panel diagnostics (Table 2).

Table 2 | Panel diagnostics and specification tests

Test	Statistic	p-value	Interpretation
Hausman test	$\chi^2 = 236.68$	< 0.001	Fixed effects preferred
Breusch-Pagan LM	$\chi^2 = 512.426$	< 0.001	Panel effects present
Modified Wald	$\chi^2 = 70{,}939.59$	< 0.001	Heteroskedasticity present
Pesaran CD	4.263	< 0.001	Cross-sectional dependence
Wooldridge test	F = 3.782	0.0627	No first-order autocorrelation at the 5% level
Mean VIF	1.35	-	No multicollinearity

Note: Calculated using STATA vers. 19.

The choice between the fixed-effects and random-effects estimators is informed by the Hausman specification test. The null hypothesis of no systematic difference between the corresponding coefficient estimates is rejected ($\chi^2 = 236.68$, $p < 0.001$), supporting the fixed-effects specification in the FE–RE comparison. The remaining diagnostics examine the error structure and cross-sectional properties of the panel.

Groupwise heteroskedasticity is assessed using the Modified Wald test. The null hypothesis of homoskedasticity is rejected ($\chi^2 = 70{,}939.59$, $p < 0.001$), indicating that the variance of the error terms differs across countries.

Cross-sectional dependence is examined using Pesaran's CD test. The null hypothesis of cross-sectional independence is rejected ($CD = 4.263$, $p < 0.001$), indicating statistically significant dependence across panel units. In the EU setting, this pattern is consistent with common developments and cross-country interconnections affecting Member States over the observation period.

First-order serial correlation is assessed using the Wooldridge test for autocorrelation in panel data. The null hypothesis of no first-order autocorrelation is not rejected at the 5% significance level ($F = 3.782$, $p = 0.0627$).

Multicollinearity among the composite predictors is evaluated using variance inflation factors (VIFs). The mean VIF is 1.35, with the individual values remaining low, indicating limited linear dependence among the predictors.

The Breusch-Pagan Lagrange Multiplier test for random effects rejects the null hypothesis of zero variance in the panel-level component ($\chi^2 = 512.426$, $p < 0.001$), providing evidence of statistically significant country-level variation relative to pooled OLS.

Driscoll-Kraay standard errors are used for covariance inference robust to heteroskedasticity and cross-sectional dependence while allowing for serial correlation. The country FE-DK specification combines coefficient estimation from within-country variation with Driscoll-Kraay inference, whereas the TWFE-DK specification additionally incorporates year effects and therefore estimates the corresponding relationships after accounting for common year-specific variation.

The empirical interpretation integrates the complementary information provided by the three estimation frameworks. Hierarchical pooled OLS characterizes associations derived from combined between-country and within-country variation and documents the incremental

explanatory contribution of the conceptual blocks. Country FE-DK focuses on within-country temporal associations after accounting for time-invariant country heterogeneity, whereas TWFE-DK additionally incorporates common year effects. Comparison across these specifications distinguishes relationships observed in the pooled country-year distribution from those estimated through within-country variation under country and year fixed effects.

Composite-index sensitivity analysis. The sensitivity analysis examines selected compositional features of SICI and GTPI within the TWFE-DK framework. The baseline specification is compared with three alternative configurations, all retaining country and year fixed effects and Driscoll-Kraay inference. The first reconstructs SICI without R&D personnel (RDPERS), examining how the estimated SICI relationship changes when its research-human-capital component is removed. The second reconstructs SICI and GTPI without the renewable-energy share (SRNWEN), which enters the two baseline indices with opposite signs. The third combines both modifications. Comparisons across the four configurations consider coefficient direction and magnitude, statistical precision, and model fit, showing how the estimated relationships vary with these selected index-composition choices.

Overall, the methodological design integrates hierarchical pooled estimation, country fixed effects, two-way fixed effects, Driscoll-Kraay inference, and composite-index sensitivity analysis within a unified empirical framework. The specifications distinguish the sources of variation underlying the estimated relationships and examine how those relationships change with the inclusion of common year effects and selected modifications to composite-index construction.

3 Research results

The empirical analysis examines the associations between business R&D intensity (BERD) and five structural dimensions represented by the composite indices: structural innovation capacity (SICI), resource and energy efficiency (REEI), green transition pressures (GTPI), fiscal and policy orientation (GFPOI), and digital business transformation (DBTI). The results are organized across hierarchical pooled OLS, country fixed-effects, and two-way fixed-effects specifications, allowing the empirical patterns to be examined across combined country-year variation and within-country temporal variation. Composite-index sensitivity analysis complements these specifications by examining how the estimated associations change under selected alternative configurations of SICI and GTPI. Preliminary inspection of the pairwise relationships between variables (see Appendix 1) shows generally linear patterns consistent with the linear econometric specifications used in the analysis.

3.1 Hierarchical regression results (pooled OLS)

The hierarchical pooled OLS models provide the initial empirical representation of the associations between the structural dimensions and BERD by combining between-country and within-country variation. The sequential introduction of the composite indices across three models documents their incremental contribution to the explained variation in BERD (Table 3). The pooled estimates are interpreted within this combined source of variation and are subsequently complemented by panel specifications that focus on within-country temporal associations.

Table 3 | Hierarchical regression results (dependent variable: ZBERD)

Variables*	Model 1	Model 2	Model 3
SICI	0.689***	0.670***	0.650***
REEI	-	0.077*	0.064
GTPI	-	0.259***	0.283***
GFPOI	-	-	0.070
DBTI	-	-	0.080*
Constant	0.000	0.000	0.000
R	0.689	0.751	0.756
R^2	0.475	0.563	0.572
Adjusted R^2	0.473	0.559	0.564
ΔR^2	-	0.088	0.008
F-statistic	266.984	126.050	77.648
Sig. (F)	< 0.001	< 0.001	< 0.001
N	297	297	297

Note: * Standardized coefficients (β) are reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ΔR^2 indicates the incremental explanatory power relative to the previous model. Calculated using SPSS vers. 26.

Model 1 shows a positive and statistically significant pooled association between SICI and BERD ($\beta = 0.689$, $p < 0.01$), with the specification accounting for 47.5% of the observed variation in the dependent variable. This coefficient characterizes the relationship between structural innovation capacity and business R&D intensity across the combined between-country and within-country variation represented in the pooled country-year observations.

The addition of REEI and GTPI in Model 2 increases the explained variation from $R^2 = 0.475$ to $R^2 = 0.563$ ($\Delta R^2 = 0.088$). GTPI displays a positive and statistically significant association with BERD ($\beta = 0.259$, $p < 0.01$), whereas REEI is positively associated with BERD at the 10% significance level ($\beta = 0.077$, $p < 0.10$). The increase in explanatory power shows that the efficiency and green-transition dimensions contribute additional information to the pooled specification beyond the structural innovation dimension.

Model 3 incorporates GFPOI and DBTI and increases the explained variation from $R^2 = 0.563$ to $R^2 = 0.572$ ($\Delta R^2 = 0.008$). SICI ($\beta = 0.650$, $p < 0.01$) and GTPI ($\beta = 0.283$, $p < 0.01$) retain positive and statistically significant coefficients, while DBTI exhibits a positive association at the 10% significance level ($\beta = 0.080$, $p < 0.10$). REEI ($\beta = 0.064$) and GFPOI ($\beta = 0.070$) are not statistically significant in the full pooled specification. Across the hierarchical sequence, the largest incremental increase in explanatory power occurs with the introduction of the efficiency and green-transition dimensions in Model 2 ($\Delta R^2 = 0.088$), followed by an additional increase associated with the fiscal-policy and digital dimensions introduced in Model 3 ($\Delta R^2 = 0.008$).

The pooled estimates therefore characterize associations derived from the full country-year variation in the sample. Their hierarchical structure documents changes in explanatory power as additional structural dimensions enter the model, while the panel specifications reported

subsequently provide complementary evidence derived from within-country temporal variation.

3.2 Country and two-way fixed-effects results

The country fixed-effects specification provides evidence on within-country temporal associations after controlling for time-invariant country characteristics. Table 4 reports the country fixed-effects estimates under conventional and Driscoll-Kraay covariance structures, complementing the pooled results with an estimation framework based on within-country variation.

Table 4 | Fixed-effects regression results (dependent variable: ZBERD)

Variables*	FE (standard)	FE (Driscoll-Kraay)
SICI	0.139* (0.091)	0.139 (0.186)
REEI	0.157** (0.011)	0.157*** (0.009)
GTPI	0.132 (0.310)	0.132 (0.418)
GFPOI	−0.022 (0.705)	−0.022 (0.691)
DBTI	0.138** (0.047)	0.138* (0.062)
Constant	0.000 (1.000)	0.000 (1.000)
Observations	297	297
Number of countries	27	27
R^2 (within)	0.0766	0.0766
F-statistic	4.40	6.83
Prob > F	0.0007	0.0051

Note: * Standardized variables are used. P-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Driscoll-Kraay standard errors allow inference robust to heteroskedasticity and cross-sectional dependence while permitting serial correlation. Calculated using STATA vers. 19.

The country fixed-effects estimates provide a different empirical configuration from the pooled results by estimating the relationships from within-country variation after accounting for time-invariant country heterogeneity. Under Driscoll-Kraay inference, REEI is positively and statistically significantly associated with BERD (β = 0.157, p = 0.009), whereas SICI (β = 0.139, p = 0.186), GTPI (β = 0.132, p = 0.418), and GFPOI (β = −0.022, p = 0.691) are not statistically significant. DBTI retains a positive coefficient and is statistically significant at the 10% level (β = 0.138, p = 0.062). The within R^2 of 0.0766 indicates that the model accounts for 7.66% of the within-country variation in BERD under this specification. Compared with the pooled estimates, the statistical evidence for SICI and GTPI is weaker when the estimation is based on within-country temporal variation, whereas REEI displays a statistically significant positive association.

The inclusion of year fixed effects extends the within-country analysis by distinguishing country-specific temporal variation from developments shared across the EU sample. Table 5 presents the country FE, country FE-DK, TWFE, and TWFE-DK estimates within this extended specification framework.

Table 5 | Country and two-way fixed-effects estimates

Variables*	Country FE	Country FE-DK	TWFE	TWFE-DK
SICI	0.139* (0.091)	0.139 (0.186)	0.038 (0.449)	0.038 (0.696)
REEI	0.157** (0.011)	0.157*** (0.009)	0.135*** (<0.001)	0.135** (0.022)
GTPI	0.132 (0.310)	0.132 (0.418)	0.115 (0.102)	0.115** (0.038)
GFPOI	−0.022 (0.705)	−0.022 (0.691)	0.016 (0.623)	0.016 (0.587)
DBTI	0.138** (0.047)	0.138* (0.062)	−0.176*** (<0.001)	−0.176** (0.030)
Country FE	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Driscoll-Kraay SE	No	Yes	No	Yes
Observations	297	297	297	297

Note: * Standardized variables are used. P-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Driscoll-Kraay standard errors are robust to heteroskedasticity, autocorrelation, and cross-sectional dependence. Calculated using STATA vers. 19 and Python 3.14.7.

The TWFE specification extends the within-country analysis by incorporating common year effects alongside country fixed effects. Under Driscoll-Kraay inference, REEI is positively and statistically significantly associated with BERD ($\beta = 0.135$, $p = 0.022$), as is GTPI ($\beta = 0.115$, $p = 0.038$), whereas DBTI exhibits a negative and statistically significant association ($\beta = -0.176$, $p = 0.030$). SICI ($\beta = 0.038$, $p = 0.696$) and GFPOI ($\beta = 0.016$, $p = 0.587$) are not statistically significant. Comparison with the country FE-DK estimates shows that REEI remains positive and statistically significant after the inclusion of year effects. GTPI remains positive and becomes statistically significant, while DBTI changes from a positive association significant at the 10% level to a negative association significant at the 5% level. GFPOI changes sign but remains statistically non-significant, whereas SICI remains positive and statistically non-significant. These results indicate that the estimated within-country associations for GTPI and DBTI differ when common year-specific variation is incorporated into the panel specification.

The contrast between pooled and fixed-effects estimates shows that the empirical associations differ according to the source of variation represented by each specification. The pooled models combine between-country differences and within-country changes over time, whereas the fixed-effects models isolate within-country temporal variation. Within the latter framework, REEI retains a positive and statistically significant association with BERD, while the statistical evidence for SICI is substantially weaker. The TWFE-DK estimates further show that the inclusion of common year effects changes the statistical evidence for GTPI and both the direction and statistical significance of the DBTI coefficient, underscoring the role of temporal specification in interpreting these within-country relationships.

3.3 Composite-index sensitivity and multicollinearity assessment

The composite-index sensitivity analysis compares the baseline TWFE-DK specification with three alternative configurations of SICI and GTPI while retaining country and year fixed

effects and Driscoll-Kraay inference throughout. The first alternative reconstructs SICI without R&D personnel (RDPERS), examining the coefficient after removal of the research-human-capital component. The second reconstructs SICI and GTPI without the renewable-energy share (SRNWEN), which enters the two baseline indices with opposite signs. The third combines both modifications within a single specification. Table 6 reports the corresponding estimates and enables comparison of coefficient direction, magnitude, statistical significance, and model fit across the four index configurations.

Table 6 | Composite-index sensitivity analysis based on TWFE-DK estimates

Variables*	Baseline TWFE-DK	SICI without RDPERS	SICI and GTPI without SRNWEN	Combined configuration
SICI	0.038 (0.696)	−0.053 (0.399)	0.001 (0.992)	−0.065 (0.233)
REEI	0.135** (0.022)	0.130** (0.017)	0.132** (0.017)	0.130** (0.015)
GTPI	0.115** (0.038)	0.090 (0.122)	0.178*** (0.003)	0.167*** (0.004)
GFPOI	0.016 (0.587)	0.016 (0.530)	0.022 (0.460)	0.022 (0.382)
DBTI	−0.176** (0.030)	−0.166** (0.025)	−0.164**(0.029)	−0.152** (0.024)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Driscoll-Kraay SE	Yes	Yes	Yes	Yes
Observations	297	297	297	297
R^2	0.121	0.125	0.134	0.150

Note: * Standardized variables are used. P-values are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Driscoll-Kraay standard errors are robust to heteroskedasticity, autocorrelation, and cross-sectional dependence. Calculated using Python 3.14.7.

REEI maintains a positive and statistically significant association across all four TWFE-DK specifications, with coefficients ranging from 0.130 to 0.135. DBTI similarly maintains a negative and statistically significant association, with coefficients ranging from −0.152 to −0.176. SICI remains statistically non-significant across the four configurations, while GFPOI also remains non-significant and displays small positive coefficients. GTPI is positive throughout the analysis: its coefficient is statistically significant in the baseline specification and in both configurations excluding the shared SRNWEN component, whereas the specification reconstructing SICI without RDPERS yields a positive but statistically non-significant coefficient ($\beta = 0.090$, $p = 0.122$). Model R^2 ranges from 0.121 in the baseline specification to 0.150 in the combined configuration. Across the alternative index representations, REEI and DBTI display consistent coefficient signs and statistical significance, whereas the magnitude and statistical precision of the GTPI association vary across configurations.

Multicollinearity diagnostics complement the panel and composite-index analyses. The mean Variance Inflation Factor (VIF) is 1.35 and the maximum VIF is 1.50, while the maximum condition index is 2.156 (Table 7). These values are below conventional diagnostic thresholds and indicate a low degree of linear dependence among the composite predictors.

Table 7 | Multicollinearity and collinearity diagnostics

Indicator	Value	Interpretation
Mean VIF	1.35	Low multicollinearity
Max VIF	1.50	Low multicollinearity
Max Condition Index	2.156	Low collinearity
Variance proportions	< 0.81	No concentrated variance pattern

The comparison across model and index specifications reveals distinct coefficient patterns for the five structural dimensions. REEI is positively and statistically significantly associated with BERD in the country FE-DK and TWFE-DK specifications and across all four TWFE-DK index configurations. SICI is positive and statistically significant in the pooled models but is not statistically significant in the country fixed-effects, TWFE, or sensitivity specifications. GTPI remains positive across the reported specifications, while its statistical significance varies with the inclusion of year effects and the alternative index configurations. GFPOI remains statistically non-significant throughout the panel and sensitivity specifications. DBTI is positive in the pooled and country fixed-effects models but becomes negative and statistically significant when common year effects are included, with the negative coefficient retained across the TWFE-DK sensitivity configurations. Together, these patterns show that the relationships between the structural dimensions and BERD differ according to the source of variation, temporal controls, and selected features of index composition represented in each specification.

4 Discussion

The discussion integrates evidence from the hierarchical pooled OLS, country fixed-effects, TWFE-DK, and composite-index sensitivity specifications to interpret the associations between the five structural dimensions and business R&D intensity. Particular attention is given to differences between associations observed across combined country-year variation and those estimated from within-country temporal variation after accounting for country and year effects. These empirical patterns provide the basis for assessing the proposed hypotheses and relating the findings to the broader literature on innovation, resource efficiency, green transition, policy orientation, and digital transformation.

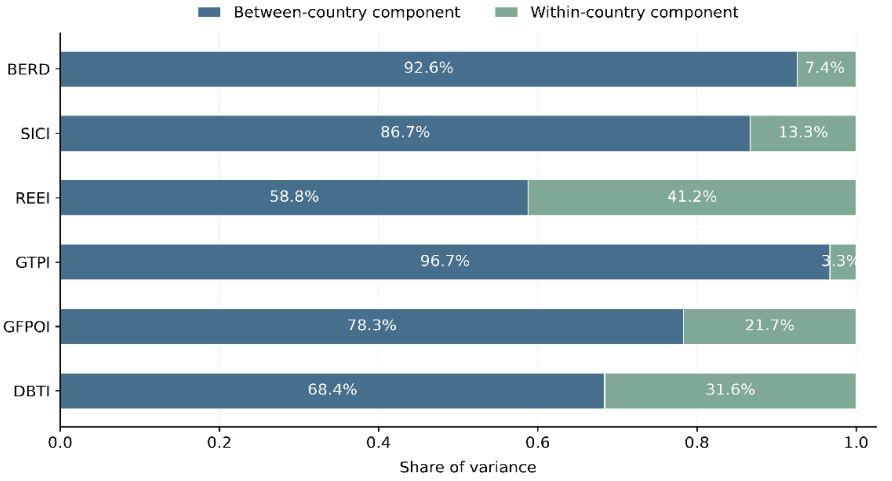
4.1 Empirical assessment of the research hypotheses

The empirical assessment of H1–H5 integrates the evidence obtained from the pooled OLS, country fixed-effects, and two-way fixed-effects specifications with the composite-index sensitivity analysis. These specifications capture distinct dimensions of the panel structure: pooled OLS combines between-country and within-country variation, country fixed effects identify associations from changes occurring within countries after accounting for time-invariant country characteristics, and the two-way fixed-effects specification additionally incorporates common year effects. The interpretation of the hypotheses therefore considers both the underlying structure of variation and the evolution of the estimated coefficients across the alternative empirical specifications.

The variance decomposition provides an empirical basis for this distinction. BERD and the five composite dimensions differ substantially in the relative contribution of between-country and within-country variation. As shown in Figure 2, between-country differences account for

92.6% of the variance in BERD, 86.7% in SICI, 58.8% in REEI, 96.7% in GTPI, 78.3% in GFPOI, and 68.4% in DBTI. Correspondingly, REEI exhibits the largest within-country component, at 41.2%, followed by DBTI at 31.6% and GFPOI at 21.7%, whereas the within-country components of SICI, BERD, and particularly GTPI are considerably smaller. These differences characterize the amount of temporal variation available for identifying within-country associations and provide context for the changes observed between pooled and fixed-effects estimates.

Figure 2 | Between-country and within-country variance components

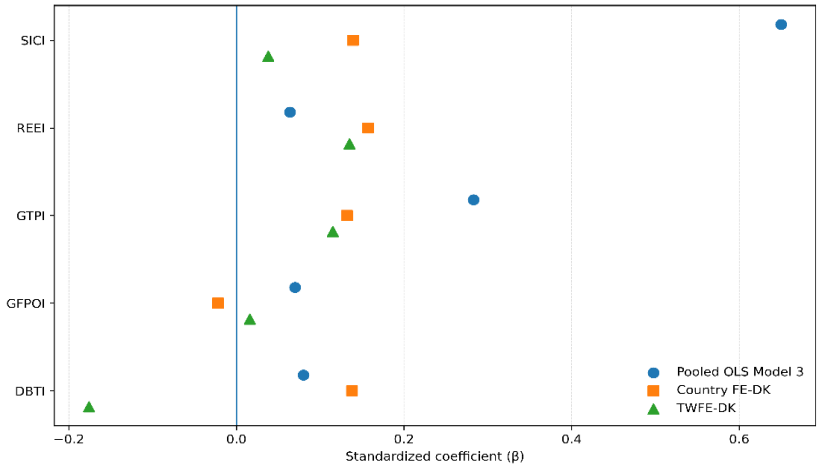


Note: The between-country component represents the share of total variance attributable to differences between country means, while the within-country component represents variation around country-specific means over time. Calculated using Python 3.14.7.

The coefficient patterns across the principal empirical specifications complement the variance decomposition in the assessment of H1–H5. Figure 3 synthesizes the estimates from pooled OLS Model 3, the country FE-DK model, and the TWFE-DK model. The comparison reveals substantial differences in coefficient magnitude and, for some dimensions, coefficient direction as the empirical focus shifts from combined between-country and within-country variation to within-country variation net of country and common year effects.

The empirical assessment of the five hypotheses reveals distinct patterns across structural cross-country variation and within-country dynamics. For structural innovation capacity (SICI), the coefficient is large and positive in the fully specified pooled model ($\beta = 0.650$, $p < 0.01$), compared with $\beta = 0.139$ ($p = 0.186$) in the country FE-DK specification and $\beta = 0.038$ ($p = 0.696$) in the TWFE-DK specification. The variance decomposition provides additional context for this contrast, with 86.7% of SICI variation attributable to between-country differences and 13.3% to within-country variation. The pooled association therefore characterizes the relationship across the combined country-year sample, whereas neither fixed-effects specification identifies a statistically significant association between within-country changes in SICI and BERD. Accordingly, **H1** is supported by the pooled evidence but not by the within-country estimates.

Figure 3 | Coefficient estimates across pooled and fixed-effects specifications



Note: The figure reports standardized coefficient estimates from pooled OLS Model 3, the country fixed-effects model with Driscoll-Kraay standard errors (Country FE-DK), and the two-way fixed-effects model with Driscoll-Kraay standard errors (TWFE-DK). Calculated using Python 3.14.7.

A different empirical configuration emerges for resource and energy efficiency (REEI). The positive association identified by the country FE-DK model (β = 0.157, p = 0.009) persists after the inclusion of common year effects (β = 0.135, p = 0.022). The variance structure of REEI provides relevant context for these estimates: 41.2% of its variation occurs within countries, the largest within-country component among the five composite dimensions. REEI therefore combines substantial temporal variation with a positive and statistically significant coefficient across both principal panel specifications. These results provide support for **H2** and indicate a positive association between within-country changes in resource and energy efficiency and BERD over time.

Green transition pressure (GTPI) presents a third pattern. Its coefficient remains positive in the pooled model (β = 0.283, p < 0.01), the country FE-DK model (β = 0.132, p = 0.418), and the TWFE-DK model (β = 0.115, p = 0.038), while statistical significance differs across specifications. At the same time, GTPI has the most pronounced cross-country structure among the explanatory indices, with 96.7% of its variance associated with between-country differences and only 3.3% with within-country variation. The TWFE-DK estimate identifies a positive association after both persistent country characteristics and common year effects are accounted for. **H3** consequently receives qualified support: the direction of the GTPI-BERD association is consistent across specifications, while its statistical precision varies with the panel structure represented by the model.

Green fiscal policy orientation (GFPOI) provides no comparable evidence of a systematic within-country relationship with BERD. Its country FE-DK coefficient is −0.022 (p = 0.691), while the TWFE-DK coefficient is 0.016 (p = 0.587). Both estimates are close to zero and statistically non-significant despite the change in sign. The results therefore do not provide empirical support for **H4** in the fixed-effects specifications.

Digital business transformation (DBTI) reveals a marked difference between specifications that do and do not account for common year effects. The pooled Model 3 coefficient is positive

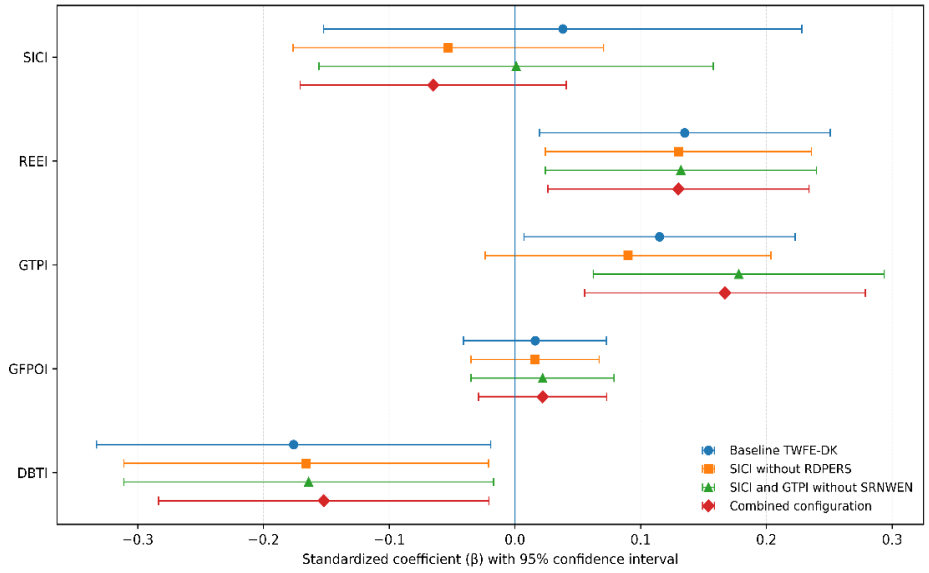
($\beta = 0.080$, $p < 0.10$), and the country FE-DK estimate is also positive ($\beta = 0.138$, $p = 0.062$). The TWFE-DK specification produces a negative and statistically significant coefficient ($\beta = -0.176$, $p = 0.030$). The variance decomposition shows that 31.6% of DBTI variation occurs within countries, indicating a substantial temporal component relative to several of the other composite dimensions. The comparison therefore shows that the estimated DBTI–BERD association changes in direction once common year-specific variation is accounted for. Accordingly, **H5** is supported by the pooled and country FE-DK estimates but not by the TWFE-DK specification, which identifies a statistically significant association in the opposite direction to that hypothesized.

Viewed jointly, the results show distinct empirical patterns across the five structural dimensions. SICI combines a positive pooled association with limited within-country variation and statistically non-significant fixed-effects coefficients. REEI has a comparatively large within-country variance component and remains positively and statistically significantly associated with BERD in both principal panel specifications. GTPI is predominantly characterized by between-country variation but has a positive and statistically significant coefficient in the TWFE-DK specification. GFPOI remains statistically non-significant in both principal panel models, whereas the DBTI coefficient changes direction when common year effects are introduced. These differences distinguish associations observed across the pooled country-year distribution from those estimated through within-country changes over time.

The composite-index sensitivity analysis extends this interpretation by examining whether the TWFE-DK coefficient structure changes under alternative representations of SICI and GTPI. Figure 4 presents the baseline estimates alongside three alternative configurations and their 95% confidence intervals: SICI reconstructed without RDPERS, SICI and GTPI reconstructed without their shared SRNWEN component, and a combined configuration incorporating both modifications. Country effects, year effects, and the Driscoll-Kraay covariance structure are retained across all four specifications, allowing the coefficient patterns to be compared under the selected changes in index composition.

The alternative index configurations produce different degrees of coefficient variation across the five structural dimensions. SICI ranges from −0.065 to 0.038 and remains statistically non-significant across all four configurations, so the alternative constructions considered here do not yield a statistically significant within-country SICI-BERD association. REEI coefficients range narrowly from 0.130 to 0.135 and remain positive and statistically significant across the four specifications, providing support for H2 under each of the selected index configurations. GTPI also remains positive across all four specifications (0.090–0.178), although its statistical precision varies with index composition. Its coefficient is statistically significant in the baseline model and in both specifications excluding the shared SRNWEN component, whereas the configuration excluding RDPERS from SICI yields a positive but non-significant estimate. The sensitivity results therefore retain the positive direction underlying H3 while showing variation in its statistical precision. GFPOI remains statistically non-significant across the four configurations, leaving the assessment of H4 unchanged. DBTI retains a negative and statistically significant coefficient in every TWFE-DK configuration (−0.176 to −0.152), with relatively limited variation in coefficient magnitude across the selected index modifications.

Figure 4 | Sensitivity of TWFE-DK coefficient estimates to alternative index configurations



Note: Points represent standardized coefficient estimates and horizontal bars represent 95% confidence intervals. The four specifications comprise the baseline TWFE-DK model, SICI reconstructed without RDPERS, SICI and GTPI reconstructed without SRNWEN, and the combined configuration. Calculated using Python 3.14.7.

The hypothesis assessment therefore reflects different empirical patterns across the five structural dimensions. H2 is supported by the positive REEI association in the country FE-DK and TWFE-DK specifications and across the alternative index configurations, while H3 receives qualified support because its coefficient remains positive but varies in statistical precision across specifications. H1 is supported by the pooled evidence but not by the fixed-effects estimates, whereas H4 is not supported across the estimated specifications. H5 is supported by the positive pooled and country FE-DK estimates but not by the TWFE-DK specification, which identifies a statistically significant coefficient in the opposite direction to that hypothesized. Taken together, the variance decomposition, coefficient comparison, and index sensitivity analysis differentiate associations observed across the pooled country-year distribution from those estimated through within-country variation after accounting for country and common year effects. This distinction provides the basis for comparison with the existing literature in Section 4.2.

4.2 Comparison with existing literature

The positive pooled association between SICI and BERD is consistent with studies linking economic development and human capital to stronger R&D activity (Kim, 2025; Orsolin et al., 2026). The panel results add a temporal distinction to this literature: the SICI coefficient becomes statistically non-significant when estimation is based on within-country variation and remains non-significant after common year effects are incorporated. The composite-index approach therefore captures a broad structural innovation configuration that is closely associated with BERD in the pooled country-year data, while the panel estimates provide limited evidence of a corresponding within-country association over the observation period.

The REEI results complement the mixed evidence reported for resource productivity and efficiency-related innovation conditions (Cardillo & Basso, 2025; Tsiapa et al., 2025). Its coefficient is positive and statistically significant in both country FE-DK and TWFE-DK and remains so across the composite-index configurations, linking within-country changes in resource and energy efficiency to changes in BERD. The difference between the pooled and panel estimates adds a temporal dimension to the interpretation of the innovation-sustainability relationship.

The positive GTPI estimates are consistent with studies associating sustainability pressures with innovation activity (Alinda et al., 2026; de Costa et al., 2025) and with the broader mechanism proposed by the Porter Hypothesis. In the present analysis, statistical significance differs between the country FE-DK and TWFE-DK specifications, while the sensitivity results show variation in statistical precision across alternative index configurations. Green-transition pressure therefore exhibits a positive association with BERD across the estimated models, with the statistical evidence varying according to temporal controls and index composition.

The absence of statistically significant GFPOI coefficients across pooled, country FE-DK, TWFE-DK, and sensitivity specifications differs from findings reporting positive innovation responses to fiscal incentives (Sun & Xu, 2026; L. Zhao et al., 2024). The macro-level construction of GFPOI captures the broader orientation of environmental taxation and climate-related investment rather than firm-specific exposure to particular incentive schemes. This difference in analytical scale may contribute to the divergence between the present estimates and firm-level evidence on fiscal support.

The DBTI results add a further temporal dimension to studies describing digitalization as an enabling condition for innovation. The positive pooled and country FE associations are compatible with this literature and with the positive direction formulated in H5, whereas the TWFE-DK coefficient is negative and statistically significant after common year-specific variation is accounted for. The comparison therefore shows that the positive DBTI–BERD relationship anticipated from the literature is not reproduced in the two-way fixed-effects specification, revealing a different within-country association once both country and year effects are incorporated.

4.3 Contribution and empirical novelty

The study contributes an integrated empirical framework in which structural innovation capacity, resource and energy efficiency, green-transition pressure, fiscal-policy orientation, and digital business transformation are represented through composite dimensions and examined within a common model of business R&D intensity. This multidimensional construction permits the empirical relationships to be evaluated jointly rather than through isolated indicators.

A further contribution lies in distinguishing pooled country-year variation from within-country temporal variation estimated with country effects and with combined country and year effects. The TWFE-DK estimates show that the statistical evidence for GTPI and the direction of the DBTI coefficient differ after common year-specific variation is incorporated. The composite-index sensitivity analysis complements this comparison by examining the coefficient patterns under selected alternative representations of SICI and GTPI. Together, these elements provide an empirical account of how the relationship between the structural dimensions and

business R&D intensity varies with the source of variation, temporal controls, and index composition.

4.4 Policy implications

The empirical findings provide policy-relevant evidence on the structural conditions associated with business R&D intensity in the European Union, particularly in the context of the green and digital transition (Palma & Scotti, 2025; Vasconcelos-Garcia & Carrilho-Nunes, 2024).

SICI and BERD strong pooled association highlight the relevance of the broader structural environment in which business R&D takes place, including economic performance, capital formation, research human capital, and renewable-energy integration. Its non-significance in the country and two-way fixed-effects specifications indicates that these structural characteristics are more clearly reflected in differences observed across the full country-year sample than in within-country changes over the observation period. From a policy perspective, this pattern emphasizes the relevance of the broader structural foundations of national innovation systems while distinguishing these cross-country characteristics from the within-country relationships estimated by the panel specifications.

REEI displays a positive and statistically significant within-country association across the country FE-DK, TWFE-DK, and sensitivity specifications. Energy productivity, resource productivity, and labour productivity therefore form part of the efficiency-related structural context associated with changes in business R&D intensity over time. The REEI coefficient remains positive and statistically significant after common year effects are incorporated, making these efficiency-related conditions relevant to the joint consideration of innovation and sustainability strategies.

The positive GTPI association in the pooled and TWFE-DK specifications is compatible with policy perspectives linking environmental and transition pressures to technological adaptation and innovation, consistent with the Porter Hypothesis (Tran et al., 2025; Zhang et al., 2024). At the same time, the statistical evidence for this positive relationship varies across the panel and sensitivity specifications according to temporal controls and index composition. Policy interpretation should therefore distinguish the broader transition environment from the effects of individual environmental instruments and recognize that the composite GTPI captures several dimensions of national environmental and energy pressure simultaneously.

GFPOI shows no statistically significant association with BERD across the estimated specifications. This result directs attention toward the design and transmission channels of fiscal and policy instruments rather than toward their aggregate orientation alone. Environmental taxation, climate-related investment, industrial policy, and innovation support may operate through different institutional and sectoral pathways that are not captured by the aggregate GFPOI-BERD relationship estimated in this study.

The DBTI results provide a relevant qualification for digital-transition policy. Positive pooled and country FE estimates coexist with a negative TWFE-DK association that remains statistically significant across the alternative index configurations. The macro-level relationship between digital transformation and BERD therefore varies once common year-specific developments are separated from country-specific temporal changes. For policy analysis, this pattern indicates that digitalization should not be treated as having a uniformly

positive relationship with business R&D intensity across alternative representations of country and temporal variation.

Taken together, the empirical evidence points to differentiated relationships between business R&D intensity and the structural dimensions examined across EU Member States. Structural innovation capacity, resource and energy efficiency, green-transition pressures, fiscal-policy orientation, and digital transformation exhibit distinct empirical patterns across pooled and within-country specifications. For policy analysis, these differences emphasize the relevance of considering structural, efficiency-related, green, fiscal, and digital dimensions in relation to the distinct sources of variation and coefficient patterns identified across the empirical specifications.

Conclusions, limitations, and future research

The study addressed the following research question: How are structural innovation capacity, resource and energy efficiency, green-transition pressures, fiscal-policy orientation, and digital business transformation associated with business R&D intensity across EU Member States, and how do these relationships differ between pooled country-year variation and within-country temporal variation? The empirical results reveal distinct patterns across these sources of variation. Structural innovation capacity (SICI) exhibits a strong positive association with BERD in the hierarchical pooled models but is not statistically significant in the country FE-DK or TWFE-DK specifications. Resource and energy efficiency (REEI) shows a positive and statistically significant within-country association under both country FE-DK and TWFE-DK estimation. Green transition pressures (GTPI) are positively associated with BERD in the pooled models and in the TWFE-DK specification, while fiscal-policy orientation (GFPOI) remains statistically non-significant. Digital business transformation (DBTI) exhibits a positive association in the pooled and country FE-DK estimates but a negative and statistically significant association in the TWFE-DK specification. Taken together, these results answer the research question by showing that the relationships between BERD and the five structural dimensions differ between pooled country-year and within-country variation and that, for some dimensions, the estimated patterns change further when common year effects are incorporated.

The main objective of the study was addressed through a multidimensional framework examining how structural innovation capacity, resource and energy efficiency, green transition pressures, fiscal-policy orientation, and digital business transformation are associated with business R&D intensity across complementary sources of country-year variation. The hierarchical pooled models identify substantial positive associations for SICI and GTPI, whereas the panel specifications reveal a different pattern when estimation is based on within-country variation. Under TWFE-DK estimation, REEI and GTPI are positively and statistically significantly associated with BERD, DBTI is negatively and statistically significantly associated with BERD, and SICI and GFPOI are not statistically significant. The comparison distinguishes relationships observed across combined country-year variation from those estimated through within-country changes after accounting for time-invariant country heterogeneity and common year effects.

The three specific objectives provide complementary components of this empirical framework. O1 is reflected in the construction of SICI, REEI, GTPI, GFPOI, and DBTI, which integrate economic and investment capacity, research human capital, resource and energy

efficiency, environmental transition pressures, fiscal-policy orientation, and digital transformation into five conceptually defined structural dimensions. In relation to O2, the hierarchical pooled models identify strong positive associations of SICI and GTPI with BERD, while the addition of GFPOI and DBTI produces a comparatively small further increase in explained variation. O3 is addressed by comparing these pooled relationships with country FE-DK and TWFE-DK estimates based on within-country variation. Under TWFE-DK, REEI and GTPI are positively and statistically significantly associated with BERD, DBTI is negatively and statistically significantly associated with BERD, and SICI and GFPOI are not statistically significant. The comparison therefore shows how the empirical relationships differ between combined between-country and within-country variation and within-country variation after accounting for country and common year effects.

Methodologically, the empirical strategy combines hierarchical pooled OLS, country fixed effects, and two-way fixed effects to distinguish complementary sources of variation in the panel. Country fixed effects account for time-invariant country heterogeneity, while the TWFE specification additionally incorporates common year effects. Driscoll-Kraay standard errors provide panel inference robust to heteroskedasticity and cross-sectional dependence while allowing for serial correlation. The composite-index sensitivity analysis examines the empirical implications of excluding RDPERS from SICI, removing the shared SRNWEN component from SICI and GTPI, and combining these modifications. Across these configurations, REEI remains positively and statistically significantly associated with BERD and DBTI remains negatively and statistically significantly associated with BERD, while the statistical evidence for GTPI varies across index configurations.

The analysis is conducted at the country level and therefore captures macro-level associations between the constructed structural dimensions and business R&D intensity rather than firm- or industry-level decision processes. The use of aggregate national data does not represent the substantial sectoral heterogeneity of business R&D activity across the European Union. Consistent sector-level BERD data disaggregated by NACE Rev. 2 are not available for the complete country-year sample used in this study, limiting the possibility of examining whether the estimated associations differ across industries. Future research based on harmonized sectoral or firm-level panels could examine such differences and provide a more granular representation of the relationships observed at the aggregate level.

The construction of the composite indices introduces additional interpretative constraints. SICI includes R&D personnel (RDPERS), an indicator that is conceptually close to BERD because research personnel and business R&D expenditure represent related dimensions of national innovation activity. Within the equal-weighted SICI construct, RDPERS contributes alongside the other components of structural innovation capacity while retaining this conceptual proximity to the dependent variable. The SICI coefficients therefore represent associations between the constructed structural innovation dimension and BERD rather than an independently identified effect of structural innovation capacity.

The composition of GTPI also requires careful interpretation. Greenhouse gas emissions (GHGE) and primary energy consumption (PEC) enter the index as absolute measures and may therefore reflect differences in country size alongside the environmental and energy pressures that the index is designed to represent. In addition, the share of renewable energy (SRNWEN) enters positively into SICI and negatively into GTPI. The same underlying indicator consequently contributes to two explanatory constructs in different conceptual roles,

creating an element of overlap between the baseline indices. The sensitivity specifications reported in Table 6 directly examine this feature by reconstructing SICI and GTPI without the shared SRNWEN component. The persistence of the principal coefficient patterns under these alternative configurations provides information on their sensitivity to this particular compositional choice, without removing the conceptual limitation from the baseline index construction.

Equal weighting represents a further methodological choice in the construction of the five composite indices. Equal weights provide a transparent and reproducible aggregation rule but implicitly assign the same contribution to each standardized component within an index. Alternative theoretical or data-driven weighting procedures could produce different composite scores and, consequently, different coefficient estimates. The sensitivity analysis partially evaluates index composition by excluding RDPERS, removing the shared SRNWEN component, and combining these modifications; it does not constitute an exhaustive assessment of alternative weighting structures. Future research could therefore compare equal weighting with alternative weighting procedures or dimensionality-reduction approaches while retaining a clear conceptual correspondence between the underlying indicators and the structural dimensions being measured.

The econometric specifications identify conditional associations rather than causal effects. Country fixed effects account for time-invariant country characteristics, year fixed effects account for shocks and developments common to the EU sample, and Driscoll-Kraay standard errors provide inference robust to heteroskedasticity and cross-sectional dependence while allowing for serial correlation. Potential endogeneity may nevertheless arise from reverse relationships, omitted time-varying factors, or simultaneous adjustment between BERD and the explanatory dimensions. Dynamic panel approaches, appropriately identified instrumental-variable strategies, or designs exploiting exogenous policy variation could extend the analysis toward causal questions.

The 2013–2023 observation window also limits the temporal scope over which structural adjustment can be evaluated. Some relationships involving innovation capacity, environmental transition, digitalization, and private R&D investment may operate with lags extending beyond contemporaneous annual associations. Future research could examine distributed-lag or dynamic specifications as longer and consistently harmonized series become available. Combining these approaches with sector- or firm-level evidence would also allow the heterogeneity of the macro-level relationships identified here to be examined across industries and firms within Member States.

The contribution of the study lies in integrating five constructed structural dimensions with complementary pooled and panel specifications and in showing that their associations with BERD differ across sources of country-year variation. The comparison between country FE-DK and TWFE-DK identifies differences in the GTPI and DBTI estimates after common year effects are incorporated, while the sensitivity analysis examines the implications of selected index-composition choices. The resulting framework connects the multidimensional measurement of innovation-related structural conditions with an econometric design that distinguishes pooled associations from within-country temporal relationships.

The empirical evidence supports a differentiated perspective on the structural context of business R&D investment in the European Union. Structural innovation capacity, resource

and energy efficiency, green-transition conditions, fiscal-policy orientation, and digital transformation display distinct associations with BERD across pooled and within-country specifications. For EU innovation policy, these patterns highlight the relevance of considering structural, efficiency-related, environmental, fiscal, and digital dimensions in relation to persistent country characteristics, common temporal developments, and country-specific changes. This multidimensional perspective situates business R&D intensity within the broader green and digital transformation of European economies.

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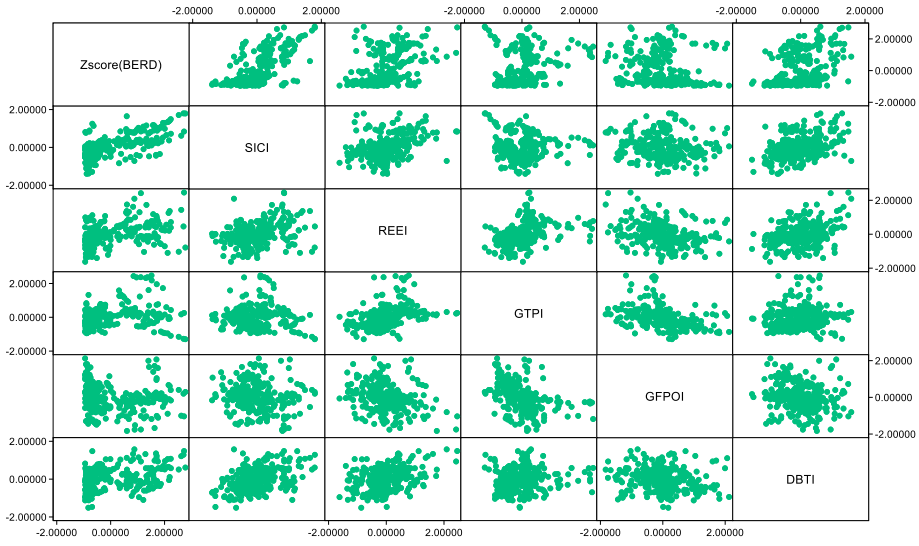
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Appendix

Appendix 1 | Pairwise scatterplot matrix of standardized model variables



Note: Created using STATA vers. 19.

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