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DIGITAL INFRASTRUCTURE AND EDUCATION AS DRIVERS OF ENTREPRENEURSHIP IN THE EUROPEAN UNION

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Abstract. In the context of accelerated digital transformation, understanding the factors that stimulate entrepreneurship at the European level has become a strategic priority. This study investigates the impact of digital infrastructure and human capital on new business density in the European Union, testing the hypothesis that these determinants operate differently depending on countries' innovation stage. The analysis is grounded in a balanced panel dataset covering 26 EU member states over the period 2010–2023, grouped into four innovation clusters according to the European Innovation Scoreboard. Empirical analysis adopts a dual econometric approach. Static relationships are estimated using a Panel EGLS framework with cross-section SUR weights to capture short-run correlations and cross-country interdependence. Dynamic relationships are examined through a Panel Autoregressive Distributed Lag (ARDL) model estimated via the Pooled Mean Group (PMG) method, allowing for the identification of long-run equilibrium effects and adjustment dynamics while accounting for structural heterogeneity. Results show substantial cross-cluster heterogeneity. For Moderate Innovators, primarily located in Southern and Central Europe, digital infrastructure acts as a clear catalyst for entrepreneurship, exerting positive effects on new business density in both the short and long run. In contrast, for Strong Innovators, digitalization displays a more complex temporal pattern, with short-run effects dominated by implementation and adjustment costs, while long-run benefits materialize as productivity gains. The analysis shows that tertiary education supports entrepreneurial entry in the short run, while its long-run effect becomes negative, reflecting rising opportunity costs and the increasing absorption of skilled labor into corporate employment. While emerging economies benefit directly from investments in digital infrastructure, mature economies require structural interventions to reduce market rigidities and better align human capital with entrepreneurial activity.

Keywords: entrepreneurship, digital infrastructure, human capital, innovation clusters, panel ARDL, European Union.

JEL Classification: L26, O33, I25.

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1. Introduction

Entrepreneurship stands as a fundamental pillar of economic dynamism and growth within the European Union, driving innovation, job creation, and social cohesion. In an increasingly interconnected global economy, the entrepreneurial landscape is profoundly reshaped by two critical forces: the acceleration of digital transformation and the quality of human capital. Digital infrastructure acts as a structural enabler, lowering entry barriers and facilitating access to global markets (Nambisan et al., 2019), while tertiary education provides the cognitive skills and absorptive capacity necessary for value-added business creation (Urbano et al., 2019). This perspective is grounded in the entrepreneurship ecosystem approach, which emphasizes that entrepreneurial outcomes depend on the interaction between infrastructure, human capital, and institutional context (Ács et al., 2025; Urbano et al., 2019). Within this framework, digital infrastructure and education are not isolated drivers but interconnected components shaping entrepreneurial dynamics across different development stages. This study provides an integrated analysis of the relationship between digital infrastructure, education, and entrepreneurship across 26 EU Member States over the period 2010–2023. In contrast to previous research that examines these factors separately, the analysis adopts a clustered approach based on the European Innovation Scoreboard (European Commission, 2025) and applies both static (Panel EGLS) and dynamic (Panel ARDL) econometric methods. This approach enables the identification of structural differences across innovation stages and allows for the empirical assessment of digital catch-up and opportunity-cost mechanisms within the European context.

Although digital infrastructure and education have been widely examined, existing studies often analyze these drivers separately or without fully accounting for structural differences across innovation stages. Evidence on their short-run versus long-run effects is also limited. This study addresses these gaps by analyzing both drivers within a unified, cluster-based European framework. The study contributes to the literature by examining digital infrastructure and education together as drivers of entrepreneurship, rather than treating them separately. It also adopts an innovation-cluster perspective based on the European Innovation Scoreboard, which allows structural differences across development stages to be captured more clearly. In addition, by combining static EGLS and dynamic PMG-ARDL estimations, the analysis distinguishes between short-run and long-run effects in the European Union.

The paper is organized into the following sections: Section 2 presents the literature review and hypothesis development. Section 3 describes the data, cluster analysis, and the econometric methodology. Section 4 and Section 5 analyze the empirical results from the static and dynamic models, including a discussion of findings and robustness checks. The final section concludes the study with policy implications specific to each innovation cluster and suggestions for future research.

2. Literature review and hypotheses development

The transition toward a digital economy has reshaped the entrepreneurial environment, increasing the role of digital connectivity and intangible resources across different innovation contexts. From this perspective, digital infrastructure and education can be understood as complementary enabling conditions that affect entrepreneurial activity through access to information, and the ability to transform opportunities into viable business initiatives.

Digital technologies and infrastructure influence entrepreneurial activity by facilitating the transition from innovation to firm formation through lower informational and transactional barriers and improved organizational alignment (Elia et al., 2020; Nambisan et al., 2019). This digital transformation is often conceptualized through frameworks such as the Digital Entrepreneurship Ecosystem Model (DEEM), which links structural infrastructure with strategic activation and human capital (Camps et al., 2026). Digital ecosystems reshape how entrepreneurs access information and coordinate actions, reinforcing the systemic role of digital infrastructure in venture creation (Autio et al., 2018). Empirical evidence from the European Union highlights a positive correlation between digital transformation, specifically connectivity, digital public services, and the integration of digital technologies and the density of new businesses (Anton, 2024; Obelovska et al., 2025). Digital infrastructure facilitates access to global markets and the development of new business models, allowing firms to deploy new knowledge and rapidly integrate relational networks (Hervé et al., 2020). Furthermore, digital platforms and information processing capabilities act as socio-technical enablers that reduce friction in the venture creation process (Sahut et al., 2021). Regarding the temporal nature of these effects, studies analyzing European countries have found that while short-run causality between ICT infrastructure and economic outcomes can be mixed or non-uniform, there is strong evidence of a long-run cointegration relationship (Pradhan et al., 2019; Asongu & Odhiambo, 2020). This suggests that the structural integration of digital technologies creates a stable equilibrium that reinforces entrepreneurial ecosystems over time, often requiring specific usage thresholds to be crossed before significant benefits materialize (Nicolescu et al., 2024). Recent evidence from European innovation clusters shows that digitalization positively affects economic performance over the long term by supporting service provision and access to markets (Dzitac et al., 2025). Widespread and reliable infrastructure is a prerequisite for these sustainable economic benefits, and connectivity is identified as a primary component driving this competitiveness (Dabbous et al., 2023). Overall, the literature indicates that digital infrastructure is positively associated with entrepreneurship, although its effects may differ across time horizons. While some studies report immediate positive effects, others suggest that the full benefits of digitalization emerge only after longer adjustment processes. These findings support the formulation of the first hypothesis.

H1: *Digital infrastructure has a positive effect on new business density, with stronger effects expected in the long run than in the short run.*

In the realm of education, Human Capital Theory posits that knowledge, and skills are primary drivers of productivity and entrepreneurial potential (Nicolescu et al., 2024). Studies focused on the immediate effects of training demonstrate that individuals with economic and entrepreneurial educational backgrounds exhibit significantly higher intentions to start businesses compared to those without such specific training (Ilieș et al., 2023). University educational environments contribute to the development of entrepreneurial skills and intentions, indicating that education can shape the propensity for entrepreneurial activity. The transition from intention to actual business creation remains dependent on broader opportunity structures and labor market conditions (Gubik, 2021). University interventions and digital skills training play a pivotal role in developing entrepreneurial capacity and self-efficacy, which are strong predictors of the intent to create new ventures in the short term (Tóth-Pajor et al., 2023; Obelovska et al., 2025). Furthermore, higher levels of education are often associated with better resource acquisition, such as access to finance and management capabilities, which facilitate exporting and business activity (Pickernell et al., 2016). The academic landscape is increasingly oriented toward the entrepreneurial university model, which complements traditional teaching and research with innovation and business creation activities (Tripa et al., 2025). This transition, however, is often constrained by bureaucratic procedures, limited funding, and cultural resistance within established academic structures, which may slow the conversion of educational capacity into entrepreneurial outcomes (Tripa et al., 2025). Furthermore, the influence of education proves to be heterogeneous across innovation clusters. As Dzitac et al. (2025) observe, the translation of workforce skills into tangible economic outcomes is not automatic, but rather conditioned by prevailing structural factors that may dampen immediate effects. Consequently, empirical analyses across the EU have observed that high educational attainment can negatively influence new business rates under certain conditions, as the availability of stable employment for the highly skilled may dampen the density of new ventures over time (Nicolescu et al., 2024). Regional human capital supports long-term entrepreneurial persistence by shaping opportunity recognition and local capabilities (Fritsch & Wyrwich, 2018). The literature suggests that the relationship between tertiary education and entrepreneurship is not uniform across time horizons. While education tends to strengthen entrepreneurial skills, intentions, and capacity in the short run, its long run effect may weaken or become negative in contexts where highly educated individuals face attractive wage-employment opportunities. These findings support the formulation of the second hypothesis.

H2: *Tertiary education is positively associated with new business density in the short run, while its long-run effect weakens or becomes negative due to opportunity cost mechanisms.*

The literature reveals that the impact of digitalization, education, and institutions on entrepreneurship is not uniform but heterogeneous across countries depending on their stage of innovation and economic development (Anton, 2024; Niebel, 2018). This perspective is consistent with the entrepreneurship ecosystem literature, which shows that entrepreneurial outcomes are shaped by the interaction of institutional quality, innovation capacity, and regional development conditions rather than by isolated factors (Ács et al., 2025). Institutional factors shape human behavior and entrepreneurial activity differently across contexts, influencing economic growth outcomes (Urbano et al., 2019). Research categorizing EU member states into different innovation tiers, such as emerging, moderate, and innovation leaders, suggests that the positive influence of digitalization on entrepreneurship is often most pronounced in emerging innovator countries or transitioning economies (Nicolescu et al., 2024). In developing EU markets like Romania, specific dynamics emerge where regional gaps in innovation capabilities remain remarkably persistent. Badulescu et al. (2024) argue that regions with higher economic growth are better positioned to attract R&D investments, creating a bidirectional relationship that can deepen inequalities between developed and lagging regions. This suggests that without consistent public and private coordination, the spillover effects of innovation remain limited in these economies (Badulescu et al., 2024). This phenomenon suggests that developing and transitioning economies can obtain substantial productivity gains from ICT investments by accelerating development processes and reducing structural gaps (Majeed & Ayub, 2018; Zghidi & Trabelsi, 2025). Conversely, in advanced economies, the threshold for digitalization to positively impact new business creation is higher, suggesting a saturation effect where basic infrastructure is no longer a primary differentiator (Nicolescu et al., 2024). According to Bai et al. (2021), digitalization generates uneven outcomes across economies, amplifying structural differences linked to institutional and innovation capacities. In highly developed sectors or regions, the limits to open innovation and knowledge collaboration may be different, influenced by transaction costs and the appropriability of knowledge

(Audretsch & Belitski, 2023). Regional policies, such as smart specialization, attempt to address these disparities by tailoring support systems to local economic contexts (McCann & Ortega Argilés, 2016). Thus, the literature indicates that the effects of digitalization and education on entrepreneurship vary across development stages and institutional settings. This heterogeneity suggests that the relationship is unlikely to be uniform across EU innovation clusters, which motivates the third hypothesis.

H3: *The effects of digital infrastructure and tertiary education on new business density differ across innovation stages, being stronger in transitioning economies and weaker or saturated in advanced economies.*

To capture the dynamics of entrepreneurial activity, the study utilizes the New Business Density indicator (New registrations per 1,000 people ages 15–64). This indicator is validated in recent specialized literature as an important measure, allowing for relevant cross-border comparisons and reflecting the frequency of new business creation in a manner sensitive to changes in the economic and regulatory environment (Anton, 2024; Nicolescu et al., 2024). Furthermore, new business density is considered a strong predictor of economic growth and employment, being used to evaluate the vitality of entrepreneurial ecosystems in diverse economic contexts (Dabbous et al., 2023). Regarding digital infrastructure, the variable Secure Internet Servers is employed as a proxy for the sophistication and security of the digital environment. The literature emphasizes that ICT infrastructure, measured by internet servers, is a critical component of economic development, facilitating secure transactions and technology-based business models (Majeed & Ayub, 2018). Pradhan et al. (2019) explicitly Includes Internet Servers (INS) among the key indicators of ICT infrastructure, demonstrating that the development of this infrastructure has a causal relationship with venture capital investments and long-run economic growth. This technical infrastructure is a prerequisite for reducing transaction costs and expanding access to global markets (Hervé et al., 2020). With respect to human capital, Tertiary Education is analyzed as a determinant of entrepreneurial capacity. According to Human Capital Theory, higher education equips individuals with the knowledge and skills necessary to identify opportunities and manage the risks associated with launching a business (Nicolescu et al., 2024). Empirical studies confirm that individuals with a university educational background, particularly in economic or entrepreneurial fields, exhibit a significantly higher intention to start new businesses, with education acting as a catalyst for transforming potential into concrete economic activity (Ilieș et al., 2023). However, the impact of education varies depending on the economic context, interacting in complex ways with digital infrastructure to influence business density (Asongu et al., 2020).

To ensure the robustness of the econometric model, it is essential to control macroeconomic factors that fundamentally influence the rate of new business creation, specifically Gross Domestic Product (GDP), trade openness, and access to private credit. Research by Anton (2024) validates the inclusion of these variables, finding that access to finance, measured as domestic credit to the private sector, has a significant positive impact on entrepreneurial activity across almost all quantiles of new business density. Regarding economic output, empirical evidence indicates that economic growth positively affects new firm registration rates, as a stable macroeconomic environment allows for the expansion of the SME sector and general prosperity.

3. Data and econometric modeling framework

The empirical analysis is based on a balanced macro-panel dataset covering 26 European Union member states over the period 2010–2023, with all variables sourced from the World Bank's World Development Indicators (WDI) (Table 1). Entrepreneurial activity is represented by New business density (new registrations per 1,000 people ages 15–64) (lnNBD), which captures formal creation of firms with potential for scalability and is suitable for cross-country panel estimation. Digital infrastructure quality is measured using Secure Internet Servers (per 1 million people) (lnDIG), reflecting the availability of trusted and secure digital environments, essential for e-commerce and digital start-ups. Human capital is represented by School enrollment, tertiary (% gross) (EDU), reflecting the level of advanced educational attainment relevant for innovation-oriented entrepreneurial activity. To control macroeconomic conditions, the model includes GDP per capita, PPP (constant 2017 international $) (lnGDP) as an indicator of economic development and demand capacity, Domestic credit to private sector (% of GDP) (DCPS) as a measure of financial depth and access to credit, and Trade Openness (% of GDP) (TRAD) to account for international openness and competitive pressure. All non-percentage variables are expressed in natural logarithms to mitigate skewness and heteroscedasticity. The selected proxies are appropriate for both conceptual and empirical reasons. New Business Density provides a comparable measure of formal firm creation across countries, while Secure Internet Servers and Tertiary Education capture key dimensions of digital infrastructure and advanced human capital. Together, these indicators offer a consistent operationalization of the entrepreneurship-digitalization-education nexus in a macro-panel EU context.

Table 1. Description of variables and data sources

Variable (Symbol)	Indicator name	Short definition	Source
New Business Density (lnNBD)	New registrations per 1,000 people ages 15–64 (log)	The number of newly registered firms with limited liability per 1,000 working-age people (ages 15–64) per calendar year.	World Bank (n.d.)
Secure Internet Servers (lnDIG)	Secure servers using TLS/SSL per 1 million people (log)	The number of distinct, publicly-trusted TLS/SSL certificates found in the Netcraft Secure Server Survey (by hosting country), per 1 million people.	World Bank (n.d.)
Tertiary Education (EDU)	School enrollment, tertiary (% gross)	Gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown.	World Bank (n.d.)
Economic Development (lnGDP)	GDP per capita (constant 2015 US$) (log)	Gross domestic product is the total income earned through the production of goods and services in an economic territory.	World Bank (n.d.)
Private credit (DCPS)	Domestic credit to private sector (% of GDP)	Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment.	World Bank (n.d.)
Trade Openness (TRAD)	Sum of exports and imports of goods and services (% of GDP)	Trade is the sum of exports and imports of goods and services. This indicator is expressed as a percentage of Gross Domestic Product (GDP).	World Bank (n.d.)

To account for structural heterogeneity across countries, the panel was grouped into four innovation-based clusters following the 2025 European Innovation Scoreboard (EIS) (European Commission, 2025):

- *Innovation Leaders*: Denmark, Finland, and Sweden. Although the Netherlands is generally classified as an Innovation Leader, it was excluded from the analysis owing to data limitations for the core explanatory variables.
- *Strong Innovators*: Austria, Belgium, Cyprus, Germany, Estonia, France, Ireland, and Luxembourg.
- *Moderate Innovators*: Czechia, Greece, Spain, Hungary, Italy, Lithuania, Malta, Portugal, and Slovenia.
- *Emerging Innovators*: Bulgaria, Croatia, Latvia, Poland, Romania, and Slovakia.

Given the dimensional characteristics of the panel (N = 26 countries, T = 14 years) and the heterogeneity in sample sizes across innovation clusters, the empirical analysis adopts a two-stage econometric framework. As a basic specification applicable to all four clusters, we employ a panel Estimated Generalized Least Squares (EGLS) estimator with cross-section Seemingly Unrelated Regressions (SUR) weighting. This approach is particularly appropriate in the European context. As noted by Baltagi (2021), this approach is particularly efficient for panels where the time dimension is relatively small compared to the cross-sectional dimension, improving the precision of coefficient estimates. Furthermore, the SUR weighting scheme allows for contemporaneous correlation between error terms across countries, addressing the issue of interdependence common in integrated economic regions like the EU (Zellner, 1962). To capture persistence and path dependence in entrepreneurial activity, the model includes the lagged dependent variable among the regressors. This dynamic specification allows current new business formation to be conditioned by past entrepreneurial outcomes, thereby reflecting the cumulative dynamics of entrepreneurial ecosystems. The general form of the estimated model is specified as follows:

$$\ln\left(\text{NBD}\right)_{it} = \alpha_i + \gamma \ln\left(\text{NBD}\right)_{i,t-1} + \beta_1 \ln\left(\text{DIG}\right)_{it} + \beta_2 \text{EDU}_{it} + \sum_{k=1}^{3} \delta_k Z_{it} + \varepsilon_{it}, \qquad (1)$$

where, i and t represent the country and year, respectively; α_i represents the country-specific fixed effects, controlling for unobserved heterogeneity; $\ln(\text{NBD})_{i,t-1}$ is the lagged dependent variable, where the coefficient γ indicates how strongly current business creation depends on its past values; $\ln(\text{DIG})_{it}$ and EDU_{it} are the core explanatory variables; Z_{it} is the vector of control variables (GDP per capita, Private Credit, Trade Openness); ε_{it} is the error term.

The Cross-Section SUR approach differs from standard panel estimators by allowing for correlation across countries in the same period. While the error terms are assumed to be well behaved within each country over time, they may be correlated across countries in a given year, reflecting the high degree of economic integration within the European Union. The EGLS estimator corrects for cross-sectional correlation and potential heteroscedasticity by applying a GLS-based estimation procedure, thereby producing more reliable coefficient estimates and inference than conventional OLS-based methods. In line with the specification tests, country-specific fixed effects are included to control for unobserved, time-invariant heterogeneity across countries. This specification ensures that the estimated relationships are not influenced by persistent structural differences between countries. Given the macro-panel structure of the data and the relatively limited number of cross-sectional units in some clusters, the EGLS-SUR framework provides a more suitable and efficient estimation approach than alternative panel estimators, particularly those relying on large cross-sectional dimensions. To assess multicollinearity, pairwise correlations and variance inflation factors were examined before estimation. The results do not indicate multicollinearity, which supports the stability of the estimated coefficients.

To strengthen the robustness of the empirical findings and to capture the dynamic behavior of entrepreneurial ecosystems, the analysis is further extended using a panel Autoregressive Distributed Lag (ARDL) framework. This approach allows for the joint modeling of short-run adjustments and long-run equilibrium relationships within a unified empirical setting, offering a flexible dynamic structure across countries. Estimation is carried out using the Pooled Mean Group (PMG) estimator proposed by Pesaran et al. (1999), which assumes homogeneity in long-run relationships while permitting heterogeneity in short-run dynamics and adjustment processes. This estimator is advantageous because it constrains the long-run coefficients to be identical across countries (assuming a common economic equilibrium) while allowing short-run coefficients and error variances to differ, thus accommodating country-specific heterogeneity (Majeed & Ayub, 2018).

The ARDL(p, q) framework is reformulated as an error correction model (ECM), enabling simultaneous estimation of long-run relationships and adjustment dynamics. The equation is specified as follows:

$$\Delta \ln\left(NBD\right)_{it} = \phi_i \left[\ln\left(NBD\right)_{i,t-1} - \theta_1 \ln\left(DIG\right)_{it} + \theta_2 EDU_{it} - \theta_3 Z_{it}\right] + \sum_{j=1}^{p-1} \lambda_{it} \Delta \ln\left(NBD\right)_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{'} \Delta X_{i,t-j} + \mu_{it}, \quad (2)$$

where, Δ is the first difference operator; ϕ_i represents the Error Correction Term (ECT), which measures the speed of adjustment towards the long-run equilibrium; θ are the long-run coefficients for Digital Infrastructure, Education and control variables; λ_{it} and $\delta_{ij}^{'}$ capture the short-run dynamic coefficients; X_{it} represents the vector of independent and control variables; j represents the lag index, denoting the time delay in years; p and q denote the optimal lag lengths chosen for the dependent and independent variables, respectively (determined via the Schwarz Info Criterion); Z_{it} represents the vector of control variables (GDP per capita, Private Credit, Trade Openness).

This dynamic specification was applied specifically to the *Strong Innovators* (N = 8) and *Moderate Innovators* (N = 9) clusters, where the time-series dimension (T = 14) and cross-sectional dimension (N) are sufficient to satisfy the asymptotic properties of the PMG estimator.

A potential methodological concern in this setting is endogeneity, particularly due to possible reverse causality between entrepreneurial activity, digital infrastructure, and economic development. For example, higher entrepreneurial density may stimulate digital investment and economic growth. This issue is mitigated, although not fully eliminated, by the inclusion of country fixed effects, lagged dependent variables, and the use of a dynamic PMG-ARDL framework that distinguishes short-run adjustments from long-run equilibrium relationships. The results should therefore be interpreted as structurally informative rather than strictly causal.

4. Regression results

Before proceeding with the regression analysis, we investigated the stationarity properties of the variables to ensure valid statistical inference. We employed the Levin, Lin & Chu (LLC) test (Levin et al., 2002), which assumes a common unit root process across the cross-sections. This test is particularly appropriate for our balanced panel data structure as it offers higher statistical power compared to individual unit root tests when the time dimension (T) is relatively short compared to the cross-sectional dimension (N). The results of the unit root test, including the t-statistics and the corresponding p-values, are summarized in Table 2.

Table 2. Panel unit root tests results (source: authors' computations based on EViews output)

Variable	(1) Innovation Leaders	(2) Strong Innovators	(3) Moderate Innovators	(4) Emerging Innovators
	t-statistic (*p-value*) *I() – the level of integration*			
New Business Density (lnNBD)	–1.66 (0.05) I(0)	–6.05 (0.00) I(0)	–3.82 (0.00) I(0)	–2.23 (0.01) I(0)
Secure Servers (lnDIG)	–0.85 (0.20) I(1)	–2.55 (0.01) I(0)	–2.95 (0.00) I(0)	–2.87 (0.00) I(0)
Tertiary Education (EDU)	–1.73 (0.04) I(0)	–6.67 (0.00) I(0)	–3.35 (0.00) I(0)	–5.13 (0.00) I(0)
GDP per capita (lnGDP)	–0.67 (0.25) I(1)	–2.24 (0.01) I(0)	–2.46 (0.01) I(0)	–0.11 (0.46) I(1)
Private Credit (DCPS)	–2.60 (0.00) I(0)	–5.27 (0.00) I(0)	–3.51 (0.00) I(0)	–6.50 (0.00) I(0)
Trade Openness (TRAD)	–7.11 (0.00) I(0)	–0.82 (0.21) I(1)	–2.06 (0.02) I(0)	–2.64 (0.00) I(0)

Note: The table reports Levin-Lin-Chu (LLC) panel unit root test statistics and corresponding p-values. I (0) –integration at levels; I (1) – stationary after first differencing.

The unit root test results show a fundamental property of the dataset that is essential for the validity of the subsequent estimations. Across all four innovation clusters, the dependent variable, New Business Density (lnNBD), is stationary at levels, I (0). The corresponding t-statistics indicate a clear rejection of the null hypothesis of a unit root, with particularly strong statistical significance for Strong Innovators (t-stat = −6.05, $p < 0.001$) and Moderate Innovators (t-stat = −3.82, $p < 0.001$), while remaining within conventional significance thresholds for Innovation Leaders (t-stat = −1.66, p = 0.048) and Emerging Innovators (t-stat = −2.23, p = 0.013). The fact that the dependent variable is stationary across all clusters supports the use of a panel EGLS model with fixed effects, as it ensures reliable estimation and reduces the risk of biased or misleading inference that may arise from non-stationary dependent variables. The stationarity properties of the explanatory variables differ across country groups, indicating substantial structural heterogeneity. In the intermediate innovation clusters, digital infrastructure (lnDIG) is stationary for Moderate Innovators (t-stat = −2.95, p = 0.00) and Emerging Innovators (t-stat = −2.87, p = 0.002). Across all four clusters, tertiary education (EDU) is integrated of order zero, I(0), indicating stationarity at levels. In contrast, non-stationarity is observed for macroeconomic indicators in both advanced and emerging economies. Within the Innovation Leaders cluster, digital infrastructure (t-stat = −0.85, p = 0.197) and GDP per capita (t-stat = −0.67, p = 0.250) are integrated of order one, I (1), while GDP per capita exhibits a similar integration pattern among Emerging Innovators (t-stat = −0.11, p = 0.455). The presence of both I (0) and I (1) variables suggests that static estimation techniques are inadequate for identifying long-run relationships, which justifies the use of the PMG-ARDL framework as an efficient tool designed to accommodate mixed orders of integration.

To test the impact of digital infrastructure and tertiary education on new business creation, we estimated the reference model using the Panel EGLS method with Cross-Section SUR weights. The comparative results are summarized in Table 3. The coefficients correspond to the specifications in Eq. (1), where β denotes the main effects and δ denotes the control variables. To ensure parsimony and limit multicollinearity in small-N clusters, alternative specifications were evaluated, and control variables were retained only when statistically significant and contributing to improved model fit according to information criteria.

The estimated models exhibit strong explanatory power, with adjusted R-squared values ranging from 0.91 for Innovation Leaders to above 0.99 for both Strong and Moderate Innovators, indicating that the selected variables capture most of the variation in entrepreneurial density. Furthermore, the lagged dependent variable ($lnNBD_{t-1}$) is positive and statistically significant across all clusters ($p < 0.01$), providing clear evidence of persistence in entrepreneurial activity and suggesting that current business creation is strongly conditioned by the existing entrepreneurial ecosystem. The findings highlight substantial heterogeneity in the determinants of entrepreneurship across country groups, confirming that the estimated coefficients vary systematically with innovation stage.

For the most advanced economies (Innovation Leaders and Strong Innovators), human capital emerges as the primary driver of new business formation. In the Innovation Leaders cluster (Denmark, Finland, Sweden), the coefficient for Tertiary Education (β_2) is positive and statistically significant ($\beta_2 = 0.012$, $p = 0.008$). This suggests that a one percentage-point increase in tertiary enrollment is associated with approximately 1.2% higher new business density. For Strong Innovators, education remains a highly significant positive predictor ($\beta_2 = 0.010$, $p < 0.001$). However, we identify a distinct constraint for this cluster regarding Trade Openness (δ_3). The coefficient is negative and statistically significant ($\delta_3 = -0.010$, $p < 0.001$). This finding suggests that, in highly open and saturated markets, strong international competitive pressures constrain new domestic firms' entry. High trade openness tends to favor large, established multinational firms with strong global competitiveness, potentially crowding out smaller entrants or increasing the efficiency threshold required for new firms to remain viable. Therefore, in Innovation Leader economies, the qualitative dimension of entrepreneurship is likely to be more relevant than the sheer number of new firm entries. The coefficient associated with digital infrastructure (β_1) differs across country groups. For Innovation Leaders, the effect is not statistically significant ($p = 0.16$), reflecting saturation effects. For Strong Innovators, the coefficient β_1 is negative and statistically significant, despite its relatively small magnitude. ($\beta_1 = -0.017$). This outcome may indicate higher entry barriers or increased compliance costs associated with complex digital ecosystems in highly regulated economies.

Table 3. Panel EGLS (Cross-Section SUR) estimation results
(source: authors' computations based on EViews output)

Variable (Coefficient)	(1) Innovation Leaders	(2) Strong Innovators	(3) Moderate Innovators	(4) Emerging Innovators
Lagged NBD (γ) $\ln NBD_{t-1}$	0.592*** (0.002)	0.622*** (0.000)	0.721*** (0.000)	0.710*** (0.000)
Secure Servers (β_1) lnDIG	0.032 (0.167)	-0.017** (0.031)	0.031*** (0.000)	–0.037 (0.138)
Tertiary Education (β_2) EDU	0.012*** (0.008)	0.010*** (0.000)	0.0003 (0.631)	0.001 (0.706)
GDP per capita (δ_1) lnGDP	–	0.870*** (0.000)	–0.653*** (0.000)	1.003*** (0.022)
Private Credit (δ_2) DCPS	–	0.004*** (0.000)	–	0.008*** (0.020)
Trade Openness (δ_3) TRAD	–0.010*** (0.000)	–	–	–
Constant (α)	0.416** (0.049)	–9.597*** (0.000)	6.579*** (0.000)	–9.129** (0.027)
Observations	39	104	117	78
Adjusted R^2	0.914	0.991	0.996	0.976
F-statistic (Prob)	69.04*** (0.00)	995.8*** (0.00)	3047.5*** (0.00)	320.5*** (0.00)

Note: The values in parentheses represent the p-values. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

The strongest validation of the digital infrastructure hypothesis is observed in the Moderate Innovators cluster. The coefficient for Secure Internet Servers is positive and highly significant ($\beta_1 = 0.031$, $p < 0.001$), indicating that this group benefits strongly from digital investment. For these economies in transition, expanding secure digital infrastructure plays a key enabling role. By contrast, the education coefficient (β_2) is not statistically significant ($p = 0.63$), suggesting that the main constraint on entrepreneurship in this cluster is related to infrastructure rather than human capital.

For Emerging Innovators (e.g., Romania and Poland), digital infrastructure (β_1) and education (β_2) are not statistically significant drivers of entrepreneurial activity ($p > 0.10$). Instead, business creation in this group is mainly explained by basic macroeconomic conditions. GDP per capita has a strong and significant effect ($\delta_1 = 1.003$, $p = 0.02$), indicating a near one-to-one relationship between economic development and new firm formation. In addition, access to finance matters, as reflected by the positive and significant coefficient on private credit ($\delta_2 = 0.008$). These results suggest that economic stability and liquidity remain prerequisites for entrepreneurship, preceding the impact of digital and educational factors.

To assess the reliability of the estimated coefficients, diagnostic tests were conducted on the regression residuals, with particular attention to cross-sectional dependence given the high level of economic integration among EU member states. Since the EGLS estimator with cross-section SUR weights explicitly accounts for this issue, residual cross-sectional dependence is not expected. This was formally evaluated using the Pesaran CD test (Pesaran, 2004), which is suitable for panels with varying cross-sectional and time dimensions and tests the null hypothesis of cross-sectional independence. The results, reported in Table 4, confirm the adequacy of the model specification.

The model validation results provide strong evidence for the robustness of the EGLS–SUR estimator. For all four clusters, the p-values associated with the Pesaran CD test are high (from 0.89 to 0.99), far exceeding the conventional 0.05 significance threshold. This indicates that we cannot reject the null hypothesis of cross-section independence. Thus, the SUR weighting procedure effectively filtered out cross-sectional correlations across countries within the same period. This confirms that the coefficients reported in the core regression (Table 3) are efficiently estimated and that the associated t-statistics are reliable, thereby supporting the validity of the structural differences observed across innovation clusters.

Table 4. Residual cross-section dependence test (Pesaran CD)
(source: authors' computations based on EViews output)

Cluster	Pesaran CD statistic	p-value	Test decision
(1) Innovation Leaders	0.0083	0.9934	Fail to reject H_0
(2) Strong Innovators	0.0817	0.9349	Fail to reject H_0
(3) Moderate Innovators	0.1369	0.8911	Fail to reject H_0
(4) Emerging Innovators	0.0589	0.9531	Fail to reject H_0

5. Dynamic panel ARDL analysis as a robustness check

Before estimating the long-run elasticities using the PMG estimator, the Pesaran et al. (2001) bounds testing procedure was applied to assess the presence of a cointegrating relationship among the variables for each cross-section. The null hypothesis of the test assumes the absence of cointegration. Following the asymptotic critical values reported by Pesaran et al. (2001) for k = 5 regressors, an F-statistic exceeding the upper bound I (1) = 4.15 at the 1% significance level indicates rejection of the null hypothesis. The results reported in Table 5 point to a heterogeneous pattern of cointegration, consistent with the economic diversity across clusters.

Table 5. Summary of ARDL bounds test for cointegration (F-Statistic)
(source: authors' computations based on EViews output)

Strong Innovators	F-Stat.	Moderate Innovators	F-Stat.
Austria	50.04824	Czech Republic	5.950706
Belgium	61.91386	Spain	1.911935
Cyprus	2.781327	Greece	<100
Germany	10.51158	Hungary	7.738411
Estonia	2.245849	Italy	11.34179
France	1.808457	Lithuania	2.678587
Ireland	0.884584	Malta	1.132169
Luxembourg	<00	Portugal	5.244409
		Slovenia	7.463826

As shown in Table 5, evidence of cointegration is present among Strong Innovators, where 4 out of 8 countries, Austria, Belgium, Germany, and Luxembourg, show F-statistics above the upper critical bound I (1), indicating a stable long-run equilibrium relationship. For Moderate Innovators, the results are even stronger, with 6 out of 9 countries, including Italy and Greece, exhibiting statistically significant cointegration, which further supports the existence of long-run relationships within this group. Although the null hypothesis is not rejected for all individual countries, the strong cointegration evidence for major economies within each cluster supports the use of the panel ARDL (PMG) estimator, which assumes a common long-run relationship while allowing for short-run heterogeneity.

To distinguish short-run dynamics from long-run equilibrium relationships and to assess the robustness of the main findings, the analysis is extended using the panel ARDL (PMG) estimator for the two largest clusters: Strong Innovators (N = 8) and Moderate Innovators (N = 9). This approach makes it possible to examine whether the relationships identified in the static EGLS specification persist over time and to estimate the speed of adjustment toward equilibrium. The long-run coefficients and the error correction mechanism (ECM) results are reported in Table 6.

Table 6. Panel ARDL (PMG) estimation results (source: authors' computations based on EViews output)

Parameters	Variable	Strong Innovators (N = 8 countries)	Moderate Innovators (N = 9 countries)
Long-Run Coefficients (θ)		Coef. (p-value)	Coef. (p-value)
θ_1	Secure Internet Servers (lnDIG)	0.156*** (0.000)	0.077*** (0.000)
θ_2	Tertiary Education (EDU)	–0.043*** (0.000)	–0.006*** (0.001)
θ_3	GDP per capita (lnGDP)	–0.977*** (0.000)	–1.141*** (0.000)
θ_4	Private Credit (DCPS)	–0.012*** (0.000)	0.002** (0.019)
θ_5	Trade Openness (TRAD)	0.006*** (0.000)	–0.003** (0.026)
Adjustment Speed (ϕ)			
ϕ	Error Correction Term (ECT)	–0.279* (0.093)	–0.358*** (0.005)
Observations		104	117

Note: ***, **, and * – statistical significance at the 1%, 5%, and 10% levels.

The dynamic estimations provide further insight into the long-run structure and adjustment mechanisms underlying entrepreneurial activity across innovation clusters. The long-run coefficients (θ) confirm the central hypothesis of the study, highlighting a positive and persistent role of digital infrastructure in shaping entrepreneurial density. For Moderate Innovators, the coefficient associated with secure internet servers is positive and statistically significant ($\theta_1 = 0.077$, $p < 0.01$), indicating that investments in digital infrastructure generate durable effects beyond short-run fluctuations. This supports recent evidence from the EU service sector, where digitalization has been found to exert a consistently positive influence on performance in the long run, acting as a strategic infrastructure for market access and efficiency (Dzitac et al., 2025). For Strong Innovators, this effect is even more pronounced ($\theta_1 = 0.156$, $p < 0.01$), indicating that once longer-term adjustments take place, the positive impact of advanced digitalization clearly dominates the short-run costs or regulatory constraints observed in the static analysis. At the same time, a saturation effect emerges with respect to general economic development, as reflected by the negative and statistically significant coefficients for GDP per capita (θ_3) in both clusters. This pattern is consistent with market consolidation in more mature economies, where economic growth primarily supports the expansion of existing firms rather than a proportional increase in new firm registrations. The positive impact of digital infrastructure on new business density observed in our models aligns with recent empirical evidence from the European Union provided by Anton (2024), who highlighted that connectivity and digital integration are fundamental drivers of entrepreneurial activity. Our findings regarding the long-run equilibrium reinforce the dynamic analysis by Pradhan et al. (2019), which demonstrated that while short-run causality can be mixed, ICT infrastructure exerts a stable and significant influence on venture capital and economic growth over time.

Human capital exhibits a time-dependent and more complex relationship with entrepreneurial activity. In contrast to the short-run positive effects identified in the static EGLS estimations, the long-run coefficients for tertiary education become negative in both clusters ($\theta_2 = -0.043$ for Strong Innovators and $\theta_2 = -0.006$ for Moderate Innovators). This pattern is economically consistent and can be interpreted through an opportunity-cost mechanism, whereby highly educated individuals in developed and transitioning economies are increasingly absorbed by consolidated corporate sectors that offer higher wages and lower risk, thereby reducing incentives for entrepreneurial entry over time. The error correction dynamics further differentiate between the two clusters. For Moderate Innovators, the error correction term is negative and significant ($\phi = -0.358$, $p = 0.005$), indicating a stable cointegrating relationship and a rapid adjustment process, with approximately 36% of any short-run disequilibrium corrected within one year. By contrast, the adjustment coefficient for Strong Innovators is negative ($\phi = -0.279$) and statistically significant at the 10% level ($p = 0.093$), indicating a slower and less uniform convergence process compared to Moderate Innovators. This weaker adjustment dynamic points to greater internal heterogeneity in convergence speeds, a finding that is consistent with the country-level ECT estimates. These results suggest that institutional complexity and regulatory rigidities in more advanced economies may contribute to a more gradual return to long-run equilibrium. While our static models indicate a positive association between tertiary education and entrepreneurship in the short run, the dynamic analysis shows a diminishing effect in the long run for advanced economies. As Tripa et al. (2025) suggest, although the entrepreneurial university model actively promotes business creation through incubators and support networks, actual outcomes are often hindered by bureaucratic hurdles and funding constraints. Consequently, highly qualified human capital may be absorbed by established corporate structures rather than generating new ventures in the long run (Tripa et al., 2025). This aligns with findings by Tóth-Pajor et al. (2023), who emphasize that while education builds capacity, the mindset and intent are heavily mediated by the surrounding ecosystem.

Overall, the PMG-ARDL results reported in Table 6 reinforce the conclusion that the entrepreneurship–digitalization–education nexus operates through cluster-specific long-run mechanisms and heterogeneous adjustment paths rather than uniform structural effects across the European Union. While the pooled results confirm a common long-run equilibrium across the EU innovation clusters, the short-run dynamics exhibit significant heterogeneity, reflecting country-specific structural rigidities. To investigate this, we analyzed the individual Error Correction Terms (ECT) for the member states within the Strong and Moderate Innovators clusters. The results, detailed in Table 7, report the speed of adjustment for each economy.

Country-level error-correction estimates indicate substantial heterogeneity in adjustment dynamics both across and within innovation clusters. Within the Strong Innovators group, adjustment speeds differ considerably, with rapid convergence observed in smaller open economies such as Austria ($\phi = -1.237$, $p < 0.01$) and Luxembourg ($\phi = -0.849$, $p = 0.019$), more moderate adjustment in Ireland and Estonia, and weak or absent correction in larger economies. The magnitude of Austria's coefficient, exceeding unity in absolute terms, suggests a very rapid adjustment process before stabilization. By contrast, Germany shows no statistically significant adjustment ($\phi = 0.104$, $p = 0.26$), while France exhibits a positive and statistically significant error-correction term ($\phi = 0.076$, $p = 0.01$), indicating divergence from the implied long-run equilibrium. This internal dispersion helps explain the weaker pooled adjustment for the Strong Innovators cluster and supports the view that institutional complexity and regulatory rigidities in large economies may slow the transmission of digital infrastructure improvements into entrepreneurial outcomes. In comparison, the Moderate Innovators cluster displays a more uniform and dynamic convergence pattern, driven by strong adjustment in major economies. Southern European countries such as Spain ($\phi = -0.809$, $p < 0.001$) and Italy ($\phi = -0.635$, $p < 0.001$) correct a large share of disequilibrium within one year, while Central and Eastern European economies, including Lithuania ($\phi = -0.906$, $p = 0.03$) and Czechia ($\phi = -0.565$, $p = 0.03$), also exhibit strong convergence mechanisms. These results suggest that Moderate Innovators display a generally responsive market structure, while Strong Innovators are characterized by internal heterogeneity, with faster adjustment in smaller economies and slower responses among the largest members. The heterogeneity observed across innovation clusters indicates that the impact of digital investment is contingent on the stage of economic development. In transitioning economies, digital infrastructure is associated with higher marginal effects on entrepreneurial activity, whereas in advanced

Table 7. Individual speed of adjustment by country
(source: authors' computations based on EViews output)

Country	Adjustment Speed (ϕ_i)	p-value	Country	Adjustment Speed (ϕ_i)	p-value
Strong Innovators Cluster			Moderate Innovators Cluster		
Austria	–1.237	0.001	Lithuania	–0.906	0.03
Estonia	–0.432	0.082	Spain	–0.809	0.00
Luxembourg	–0.849	0.019	Italy	–0.635	0.00
Ireland	–0.093	0.046	Czechia	–0.565	0.031
France	0.076	0.011	Greece	–0.195	0.05
Germany	0.104	0.267	Malta	–0.088	0.084
Belgium	0.215	0.239	Hungary	0.149	0.503
Cyprus	–0.02	0.763	Portugal	–0.019	0.909
			Slovenia	–0.151	0.553

economies its influence is more limited, reflecting saturation effects. This pattern is consistent with empirical evidence showing that mature markets often exhibit inertia, where structural strengths outweigh marginal digital improvements (Dzitac et al., 2025). Moreover, Badulescu et al. (2024) identify a bidirectional long-run relationship between economic growth and R&D expenditures, suggesting that in regions such as North-West Romania, innovation-led development remains conditional on broader economic accumulation. These findings support the view that institutional and structural factors shape entrepreneurial outcomes in different ways across stages of economic development (Urbano et al., 2019).

6. Conclusions and policy implications

This study provides a differentiated and dynamic assessment of the relationship between digital infrastructure, human capital, and entrepreneurial density across European Union innovation clusters. By integrating static EGLS estimations and dynamic PMG-ARDL models, the analysis demonstrates that the entrepreneurship-digitalization-education nexus is strongly contingent on innovation stage and time horizon. The results confirm that short-run and long-run effects may differ not only in magnitude but also in direction, underscoring the importance of dynamic modeling when evaluating entrepreneurship drivers. While digital infrastructure consistently supports entrepreneurial activity in transitioning economies, its effects in more advanced contexts materialize primarily in the long run, following structural adjustment processes. Similarly, tertiary education exhibits a time-dependent role, supporting entry in the short run but displaying a negative long-run association in more developed clusters, consistent with opportunity-cost mechanisms and labor market absorption effects.

For Innovation Leaders, digital infrastructure and tertiary education do not emerge as significant short-run drivers of new business density, reflecting saturation effects in highly mature ecosystems. Consequently, H1 and H2 are not supported for this cluster, suggesting that additional investments in digitalization or education are more likely to influence entrepreneurial quality than entry rates. In the case of Strong Innovators, digital infrastructure shows weak or negative short-run effects but a strong positive long-run impact, which conditionally supports H1 once adjustment dynamics are considered. Education contributes to entrepreneurial entry in the short run but becomes negative in the long run, providing dynamic support for H2 through an opportunity-cost mechanism. For Moderate Innovators, digital infrastructure has a positive and significant effect in both the short and long run, offering strong support for H1. Education does not constrain entrepreneurship in the short run but shows a weak negative long-run association, lending partial support to H2. Finally, for Emerging Innovators, entrepreneurial activity is mainly shaped by macroeconomic fundamentals rather than knowledge-economy factors, leading to the rejection of H1 and H2 and indicating that a minimum level of economic stability is required before digital and educational investments become effective.

The results indicate that the differences between static and dynamic estimations reflect meaningful time-related effects rather than problems with model specification. For Moderate

Innovators, the positive effects of digital infrastructure in both the short and long run point to high returns on digital investment and a strong capacity to absorb new technologies, consistent with the digital catch-up hypothesis. By contrast, the sign change observed for Strong Innovators highlights the role of adjustment costs and institutional constraints, which limit entrepreneurial entry in the short run but are gradually offset by productivity gains and network effects over time. While education encourages entrepreneurial entry in the short run, its negative long-run association reflects a shift of skilled labor toward established firms offering higher wages and lower risk. Taken together, these results confirm H3 and show that the relationship between entrepreneurship, digitalization, and education depends on innovation stage, institutional setting, and adjustment capacity, rather than following a single pattern across the European Union.

From a policy perspective, the results suggest that entrepreneurship strategies should be adapted to the level of economic and innovation development. For Moderate Innovators, expanding digital infrastructure can generate both short-run and long-run gains in entrepreneurial activity. For Strong Innovators, digitalization policies are more effective when combined with institutional reforms that lower adjustment costs and regulatory complexity, implying a reorientation from the number of new firms toward their quality and growth potential. In Innovation Leaders, where saturation effects are evident, policy efforts should focus on frontier innovation and high-growth ecosystems rather than increasing firm entry. For Emerging Innovators, macroeconomic stability and access to finance remain key conditions, indicating that basic economic policies need to be in place before digital and educational investments can fully support entrepreneurship.

The study is subject to certain limitations that should be considered when interpreting the results. Entrepreneurial activity is captured through new business density, which reflects firm entry but not subsequent performance or innovation quality, while the cluster-based framework may abstract from institutional differences within clusters. In this context, future research could extend the analysis by incorporating post-entry performance indicators and more detailed measures of digital capabilities, education, and regulatory environments, thereby refining the understanding of how digitalization and human capital shape entrepreneurial dynamics across heterogeneous economies.

Authors contribution

The paper is a result of a collaborative work. CS, RS, AB and FO conceived the study, CS, RS, DB, AB and FO reviewed the literature, SD and RS did the data analysis. SD, CS, RS, DB wrote the first draft. All authors revised the paper and prepared the final article.

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