

# The State of European Entrepreneurship: Trends in Quantity and Quality in France, Germany, and the UK (2009–2023)

Massimo G. Colombo<sup>1</sup>, Lena F  ner<sup>2,3,4</sup>, Massimiliano Guerini<sup>\*1</sup>, Hanna Hottenrott<sup>2,3</sup>, and Daniel Souza<sup>1</sup>

<sup>1</sup>Department of Management, Economics and Industrial Engineering, Polytechnic University of Milan, Via Raffaele Lambruschini, 4/B, 20156, Milan, Italy

<sup>2</sup>Department Economics of Innovation and Industrial Dynamics, Leibniz Centre for European Economic Research (ZEW), L 7 11, 68161, Mannheim, Germany

<sup>3</sup>School of Management, Technical University Munich, Arcisstr. 21, 80333, Munich, Germany

<sup>4</sup>IAB Institute for Employment Research, Regensburger Str. 104, 90478, Nuremberg, Germany

July 14, 2025

## Abstract

This paper investigates the quantity and quality of entrepreneurial activity across rural and urban regions in France, Germany, and the United Kingdom between 2009 and 2023. Using comprehensive business registry data and a predictive analytics framework, we estimate both the number of new firm registrations (entrepreneurial quantity) and the growth potential of these ventures (entrepreneurial quality). Our analysis reveals substantial heterogeneity in entrepreneurial outcomes across countries and regions in Europe. While factors such as GDP per capita, access to venture capital, and educational attainment are positively associated with higher-quality entrepreneurship in urban areas, these relationships are significantly weaker in rural regions. These findings underscore the importance of ecosystem-wide support strategies tailored to regional contexts, offering valuable insights for policymakers aiming to foster high-growth entrepreneurship.

**Keywords:** Entrepreneurial Ecosystem; Regional Innovation; Knowledge Spillover

**JEL codes:** L26; R12; O18

**PRELIMINARY DRAFT — please do not cite or distribute**

---

\*Corresponding author. Email address: massimiliano.guerini@polimi.it.

This study was funded by the European Union - NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS -Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 – CUP D13C22002160001). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

# 1 Introduction

Entrepreneurship is widely recognized as a central driver of regional economic growth and innovation, with the capacity to foster competitiveness and reduce development disparities between urban and rural areas (Content et al., 2020; Acs and Armington, 2004). Over the past two decades, growing academic and policy interest has emphasized the pivotal role of startups in shaping regional development trajectories (Feldman, 2001; Glaeser et al., 2015). In parallel, significant progress has been made in measuring entrepreneurial activity. Recent studies by Guzman and Stern (2020) and Andrews et al. (2022) have advanced our understanding by shifting focus from the sheer quantity of new firms to their quality—namely, the likelihood that a startup will scale and deliver long-term economic impact. This shift reflects a broader recognition that entrepreneurial outcomes are highly skewed: a small number of high-growth firms typically generate a disproportionate share of innovation, employment, and value creation (Kortum and Lerner, 2000; Samila and Sorenson, 2011). Consequently, evaluating entrepreneurial ecosystems requires accounting for both the number of startups and their potential for growth.

As highlighted by Andrews et al. (2022) and Tartari and Stern (2021), entrepreneurial ecosystems operate across multiple geographic scales: from localized innovation hubs, such as those surrounding research universities, to broader regional, national, and transnational contexts. Effective empirical assessments must therefore take into account both spatial heterogeneity and the inherently lagged nature of entrepreneurial success, which often materializes over a decade or more. Despite growing interest in these dynamics, most empirical work has focused on the United States, leaving entrepreneurial ecosystems in Europe relatively understudied, particularly with regard to their capacity to produce high-growth firms. This gap is particularly relevant, given that the lack of high-growth startups is frequently cited as one reason behind Europe’s lag in innovation-led economic performance. Thus, addressing this issue has important policy implications.

This study contributes to filling this gap by providing novel empirical evidence on the drivers of entrepreneurial activity in Europe’s three largest economies—the United Kingdom, Germany, and France. Specifically, we assess both the quantity and quality of entrepreneurial activity across regions, defining quantity as the number of newly registered businesses and quality as the number of growth-oriented firms—those exhibiting a higher potential for expansion at or near founding (Guzman and Stern, 2020). We then examine the local factors associated with these outcomes, focusing on the core components of regional entrepreneurial ecosystems. These include physical and digital infrastructure; access to knowledge; and the availability of key resources, such as human, social, and financial capital. We also consider institutional conditions, such as the quality of governance, entrepreneurial culture, and local networks (Stam and Van De Ven, 2021). By capturing both embedded regional features and broader spatial dynamics, our study aims to offer a comprehensive understanding of the institutional and contextual determinants of entrepreneurial performance in Europe.

Our analysis builds on the predictive analytics framework developed by Guzman and Stern (2020) to estimate the growth potential of firms at the time of founding. We apply this methodology

to business registry data from the United Kingdom, Germany, and France, spanning the period 2009 to 2023. The focus is on limited liability companies, a common legal form across all three countries and one typically associated with greater growth orientation. For the UK, we use Companies House data, which provides detailed firm demographics and records of corporate events such as insolvencies, acquisitions, and capital structure changes. For Germany, we rely on the Mannheim Enterprise Panel, a longitudinal dataset based on the German Business Registry and maintained by Creditreform. In France, we combine firm-level data from the SIRENE registry with BODACC, which documents mergers, acquisitions, and legal proceedings. Together, these harmonized datasets capture more than nine million firm births over the 2009–2023 period, enabling a robust, comparative assessment of entrepreneurial quantity and quality across Europe’s three largest economies.

Our findings reveal substantial heterogeneity in entrepreneurial quality both across and within countries. At the cross-country level, traditional drivers of high-growth entrepreneurship—such as GDP per capita, venture capital availability, and educational attainment—are significantly associated with better entrepreneurial outcomes in France, and to a lesser extent in the UK and Germany. Notably, France also exhibits a higher share of rural entrepreneurial activity, both in terms of startup quantity and quality-adjusted measures. Within countries, rural regions consistently display lower levels of quality-adjusted entrepreneurship, underscoring the importance of a holistic ecosystem approach to foster high-growth ventures outside urban centers. However, differences in data granularity, regional structures, and rural definitions across countries influence the robustness of these relationships and highlight the need for tailored policy interventions and further research into region-specific entrepreneurial dynamics.

This study contributes to two main strands of literature. First, it advances research on entrepreneurial dynamics and firm growth by providing the first large-scale, systematic estimation of entrepreneurial quality in Europe. It extends recent work on firm-level growth prediction ([Andrews et al., 2022](#); [Guzman and Stern, 2020](#); [Tartari and Stern, 2021](#)) and complements longstanding contributions on the role of entrepreneurship in regional development ([Glaeser et al., 2010](#); [Samila and Sorenson, 2011](#)). By applying a harmonized methodology to regions accounting for roughly 52 percent of the EU’s GDP, this work fills a critical gap in a literature that remains predominantly focused on the U.S. context.

Second, the study contributes to the literature on regional innovation and entrepreneurial ecosystems ([Feldman, 2001](#); [Audretsch et al., 2021](#); [Lerner, 2009](#); [Stam, 2015](#)). It examines the structural and institutional factors that underpin the emergence of high-growth firms, highlighting how components such as infrastructure, human capital, networks, and regulatory environments shape entrepreneurial outcomes. In doing so, it informs both theoretical understandings of ecosystem dynamics and policy debates around fostering innovation-led regional development across diverse European contexts.

The remainder of the paper is structured as follows. The next section introduces the measures of entrepreneurial quantity and quality and presents the business registry data. We then outline the methodology of the empirical analysis. This is followed by a presentation of descriptive statistics

and preliminary findings.

## 2 Measuring Entrepreneurial Quantity and Quality Using Business Registry Data

### 2.1 Business Registry Data

Our analysis relies on business registries from UK, Germany, and France, from 2009 to 2023.<sup>1</sup> We focus on limited liability business entities, which are the ones that take a form that are more likely to have successful growth outcome and that are common legal forms across countries.

For the UK, we use the Companies House (CH) database, the official business registry including basic demographic information of active firms (name, location, year of incorporation) and information on person with significant control, officers (request access) and accounts (only electronically submitted). The CH database goes back to 1844, but reliable data can be taken since 1987. Substantial change to the register following the introduction of the Companies Act 2006 was implemented from October 2009. The total active firms in the register at the end of March 2024 was 5,350,759 and private limited companies have accounted for over 95% of corporate bodies on the register. We can complement data from CH with information insolvency, filings, striking off, dissolutions, reinstatements, takeovers and transfers, changes in capital structure can be collected from The Gazette, the UK official public record. Data from companies' public records is available from 1998.

For Germany, we use the Mannheim Enterprise Panel (MUP), a dataset that contains information on 9,361,298 firms that are or were economically active in German from 1995 to 2023, namely: complete address, number of employed persons, amount of sales, legal form, five-digit industry sector code (NACE rev. 2), date of foundation, date of closure, data of insolvency procedures, shareholder structure and information. Balance sheet information is available for a subset of medium sized corporations and company groups who publish this information. The MUP builds on the German Business Registry and is collected by Creditreform the biggest German business rating agency.

For France, we use different datasets: SIRENE (Système informatisé du répertoire national des entreprises et des établissements), National Enterprise and Establishment Register Database, which is managed by Insee and records the identity of all enterprises, and their establishments located in Metropolitan France. Foreign companies with a representative or activity in France are also recorded in it. It is an administrative database that contains the universe of firms in the private sector since 1987. For each firm, it provides the date of creation (defined as the registration date), the location of the headquarter at the zip-code level, a four-digit industry code and the number of employees when created. We will complement SIRENE data with information from the BODACC (Le bulletin officiel des annonces civiles et commerciales), which is a dataset with the information on all announcements published since 2008 which publishes documents recorded in the Commercial and business Register (RCS): Sales and Divestiture; Registration and establishment creation; Amendments and deletions

---

<sup>1</sup>Data coverage is limited to the period 2010–2020 for the UK and 2009–2022 for Germany due to concerns regarding data representativeness.

of natural or legal persons listed in the Trade and businesses Register (SCR); Collective procedures, conciliation procedures, professional recovery procedures; Notice of deposit of businesses' accounts.

## 2.2 Entrepreneurial Quantity and Quality

Following the approach of (Guzman and Stern, 2020), we consider the quantity and a quality-adjusted measure of entrepreneurship by aggregating business registry data at the regional level. Using this information, we can measure entrepreneurial quantity  $N_{rt}$  as the number of new business registrations in area  $r$  and year  $t$ . For each business registrant, we then apply a predictive analytics approach to estimate its quality by linking the growth outcome a few years after foundation (including survival, mergers & acquisitions, and IPOs) to firm characteristics in the founding year retrieved from observable business registry data and from secondary data sources.

Specifically, we estimate entrepreneurial quality for firm  $i$ , born in region  $r$  at time  $t$  with start-up characteristics  $H_{irt}$  and growth outcome after  $s$  years  $g_{ir(t+s)}$  as:

$$\theta_{irt} = Pr(g_{ir(t+s)}|H_{irt}) = f(\beta H_{irt}) \quad (1)$$

To estimate this equation, we need to observe business characteristics  $H_{irt}$  and growth outcomes  $g_{ir(t+s)}$ . The business characteristics that we consider in year  $t$  (that are likely to be related to the growth outcome in  $t + s$ ) are the following: name (length and eponymy), legal status (corporation, limited liability company or others), industry of operation, and intellectual property (patents). For growth outcomes, we consider mergers and acquisitions and IPO within  $s$  years from the founding date.

Then, using these observable firms' characteristics and growth outcomes, we can estimate  $\hat{\theta}_{irt}$ , that captures entrepreneurial quality as the probability of a new business achieving growth outcome given start-up characteristics. Using this measure of entrepreneurial quality, we calculate the Entrepreneurial Quality Index (EQI), which is the average quality of an area-year:

$$EQI_{rt} = \frac{1}{N_{rt}} \sum_{i \in I_{rt}} \hat{\theta}_{irt} \quad (2)$$

where  $I_{rt}$  represents all the active business in area  $r$  and year  $t$  and  $N_{rt}$  the number of new firms in that region-firm.

Finally, we use the EQI to measure the Regional Entrepreneurship Cohort Potential Index (RECPI), which measures the overall growth potential of a firms in a region-year:

$$RECPI_{rt} = EQI_{rt} \times N_{rt} \quad (3)$$

The RECPI captures the number of expected growth events in a region-year given the start-up characteristics of a cohort at foundation. Together, these measures will enable us to map the state of entrepreneurship at the regional level and identify different levels of success.

### 3 Empirical strategy

We exploit the panel structure of the data using fixed effects estimations to compare the performance of different regions and how it is associated with the characteristics of each regional ecosystems. Following (Tartari and Stern, 2021), we can use a fixed effects panel estimator in the form of the model:

$$Y_{rt} = \beta X_{r(t-1)} + \alpha_r + \gamma_t + \epsilon_{rt} \quad (4)$$

where  $Y_{rt}$  is the measure of local entrepreneurial activity (quantity N or the quality-adjusted measure RECPI),  $X_{r(t-1)}$  is the set of time-varying characteristics of the entrepreneurial ecosystem of the region,  $\alpha_r$  are region fixed effects and  $\gamma_t$  year fixed effects. Our parameters of interest are  $\beta$ , which are the vector containing estimates of the association between our measure of local entrepreneurial activity and the embedded factors of each area that could explain the quantity and quality of business activity in these regions.

In our analysis, we explicitly distinguish rural areas from other regions by using the Eurostat Urban-Rural typology classification based on the NUTS 3 level<sup>2</sup>, and include interaction terms to capture how the characteristics of rural areas interact with other factors influencing entrepreneurial activity.

The factors influencing entrepreneurship in regions include: (1) regional economic performance, (2) financial accessibility (such as venture capital), (3) sector specialization, (4) population density, (5) availability of human capital (*i.e.*, the proportion of tertiary-educated populations), (6) social capital (e.g., the number of de-novo and serial entrepreneurs), (7) knowledge resources (e.g., universities, patents, and scientific publications), and (8) government and corporate support for local entrepreneurship.

### 4 Data and Entrepreneurial Quality Estimates

We draw on multiple sources to construct our dataset on regional entrepreneurial activity. Regional economic performance and population density at the NUTS3 level are retrieved from the Annual Regional Database of the European Commission (ARDECO). ARDECO primarily relies on official data from Eurostat but it also incorporates data from supplementary sources and estimates generated using various methodologies (<https://urban.jrc.ec.europa.eu>). Data on the availability of tertiary education among graduates comes from the ETER dataset of the European Higher Education Sector Observatory (<https://national-policies.eacea.ec.europa.eu/eheso>). Information on venture capital availability is extracted from the VICO database, a proprietary resource developed at Politecnico di Milano, supported by the RISIS and RISIS2 projects, funded by the European Commission under the FP7 and Horizon 2020 programs. The VICO database includes data on

---

<sup>2</sup>In the descriptive statistics we also use the DEGURBA classification based on Local Administrative Units to assess the level of rural entrepreneurial activity in the selected countries.

VC-backed firms founded after 1988 in EU countries, the UK, and Israel, which received their first round of venture capital between 1998 and 2021, before reaching 10 years of age.

#### 4.1 Legal Forms and Limited Liability Structures

Table 1 summarizes the distribution of legal forms across countries, focusing on structures offering limited liability, which are particularly relevant for high-growth and risk-intensive entrepreneurial ventures.

Table 1: Legal form by country

	Share	Nb. Firms
<b>Panel A: Germany</b>		
GmbH	60.1%	765,404
UG	24.2%	308,449
GmbH & Co. KG	12.9 %	164,235
Limited	2.1%	25,924
AG (Public Ltd. Company)	0.7%	9,455
<b>Panel B: UK</b>		
Private Limited Company	99.9%	4,909,095
Public Limited Company	0.08%	3,895
European Public Limited-Liability Company (SE)	<0.01%	41
United Kingdom Societas	<0.01%	9
Private limited company (SECT. 30)	<0.01%	1
<b>Panel C: France</b>		
Société par actions simplifiée	50.3%	1,507,013
Société à responsabilité limitée (SARL)	49.5%	1,483,163
Société anonyme à conseil d'administration	0.1%	3,352
Société anonyme à directoire	0.01%	235
Société européenne	<0.01%	10

In the UK, limited liability is primarily available through four legal forms: Private Limited Company (Ltd), Public Limited Company (PLC), European Public Limited-Liability Company (SE), and United Kingdom Societas. The vast majority of firms - over 99% - are registered as Private Limited Companies. These are the most common structure for small and medium-sized businesses due to minimal capital requirements (no minimum share capital), simple registration procedures, and flexible governance. Public Limited Companies (PLCs) are designed for larger firms aiming to raise capital from public markets. They require a minimum share capital of £50,000, at least two directors, and adherence to stricter reporting and governance standards. While SEs and UK Societas forms exist, they are rarely used and became even less relevant post-Brexit, given their basis in EU corporate law. Some legacy forms like Private Limited Company under Section 30 exist



for specific cases, but they are practically negligible in number.

In Germany, five legal forms benefit from limited liability: GmbH & Co. KG, GmbH, AG, UG, and UK limited. The main limited liability structures are the GmbH, AG, and UG. The GmbH is popular for small and medium-sized businesses, requiring €25,000 in share capital, notarized articles of association, and commercial register entry. The AG targets larger companies with a minimum of €50,000 in share capital, a management board, and a supervisory board. The UG, a “mini-GmbH,” is ideal for startups, requiring only €1 in share capital but must retain 25% of profits until it reaches €25,000 in capital. The GmbH & Co. KG combines the advantages of a GmbH with a limited partnership, offering flexible management and capital structures. Its liability is limited to the company’s assets, and it is taxed as a partnership. It allows for external capital contributions and flexible shareholder changes, with the added benefit of book-value transfers for business assets. UK limited companies were once popular in Germany due to low capital requirements and limited liability, but their relevance has decreased post-Brexit. Limiteds are no longer recognized in Germany unless their principal place of business is within the EU, and the introduction of the UG has reduced the appeal of the UK limited in Germany.

In France, limited liability is provided mainly through five legal forms: Société par actions simplifiée (SAS), Société à responsabilité limitée (SARL), Société anonyme à conseil d’administration (SA), Société anonyme à directoire, and the Société européenne (SE). The SAS is the most popular form, accounting for over half of limited liability firms. It offers flexible governance with few legal constraints, making it ideal for startups and SMEs. There is no minimum capital requirement, and it allows both individuals and corporations as shareholders. The SARL is the traditional form for small and family-run businesses, also with low capital requirements (as low as €1), but with more rigid management structures than the SAS. The SA forms are used by larger firms. The SA with a board of directors and the SA with a management board and supervisory board both require a minimum share capital of €37,000 and are suited for firms with public offerings. The Société européenne (SE) is rarely adopted and primarily relevant to companies operating across EU member states.

## 4.2 Trends in Startup Creation and Growth Events

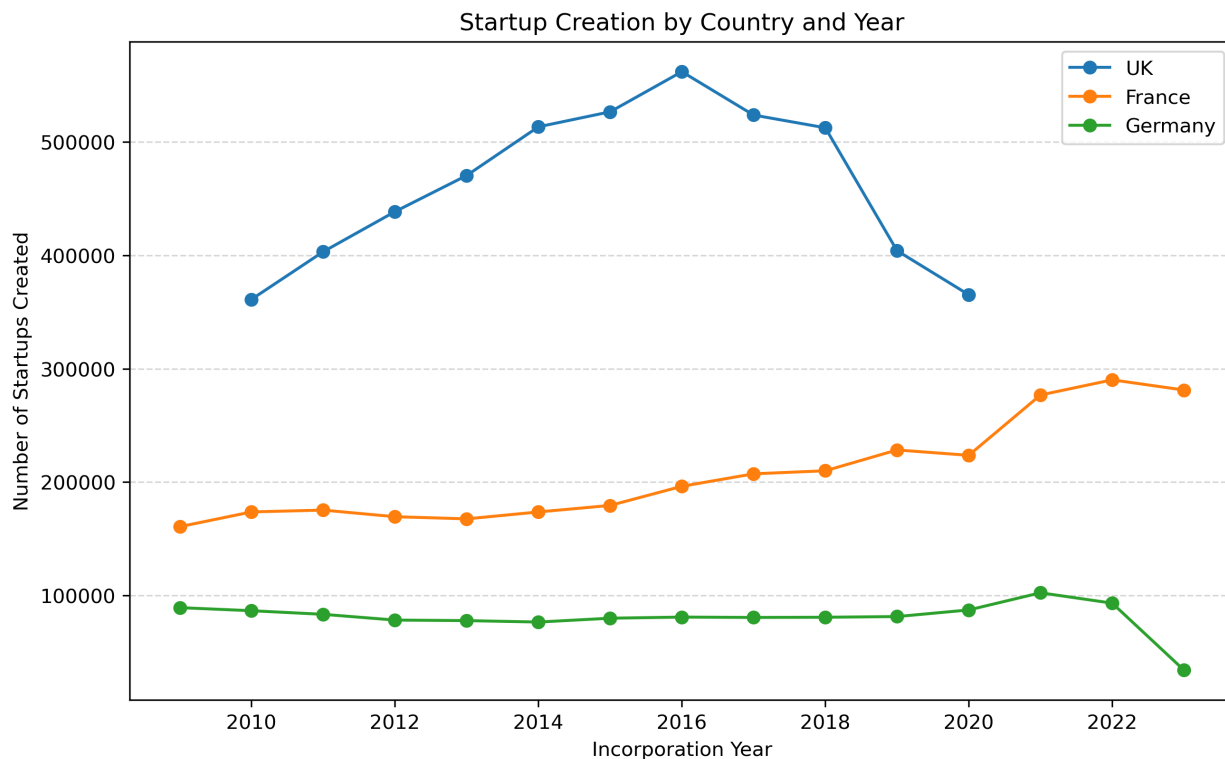
The Figure 1 illustrates annual startup creation trends in the United Kingdom, France, and Germany from 2009 to 2023, revealing notable differences in entrepreneurial dynamics across these major European economies. The United Kingdom consistently exhibited the highest number of new startups throughout the period, with a marked increase peaking around 2016 at approximately 560,000 startups. However, this upward trend reversed after 2016, with a pronounced decline observed particularly after 2019, resulting in a reduction to roughly 360,000 startups by 2023. In contrast, France demonstrated a steady and sustained growth in startup formation, beginning at about 160,000 in 2009 and rising to nearly 290,000 by 2022, with only a slight decrease in 2023. This suggests a strengthening entrepreneurial ecosystem in France, especially in the post-2020 period. Germany, meanwhile, maintained relatively stable but lower levels of startup creation compared



to the other two countries, fluctuating between 80,000 and 90,000 startups annually until 2020, followed by a modest increase in 2021 and then a sharp decline to below 50,000 startups in 2023.

Collectively, these trends highlight the UK’s declining startup momentum in recent years, France’s emergence as a growing hub for new ventures, and Germany’s recent contraction after a period of stability, reflecting the heterogeneous nature of entrepreneurial activity and possibly the influence of country-specific policies, economic conditions, and external shocks.

Figure 1: Startup Formation Year by Country and Year (2009-2023)

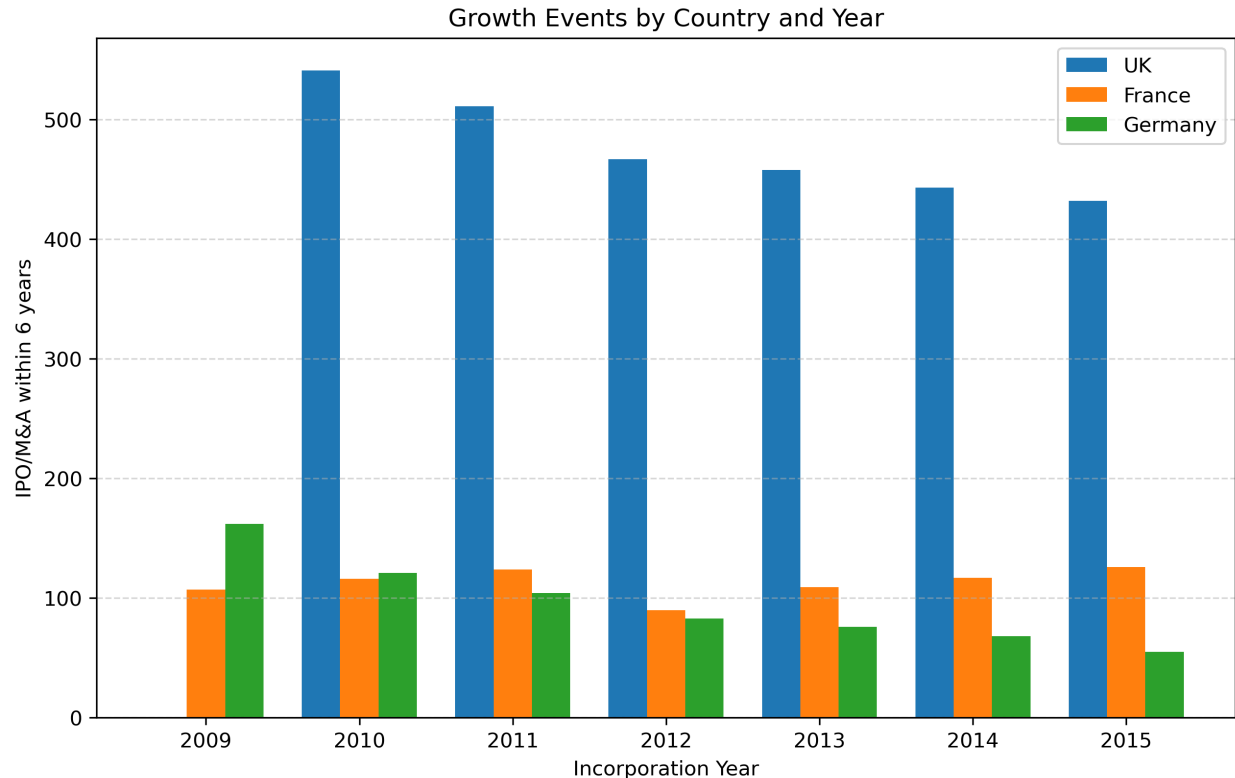


Notes:

Figure 2 displays the number of startup growth events—defined as initial public offerings (IPOs), mergers, or acquisitions occurring within six years of incorporation—for the United Kingdom, France, and Germany across cohorts founded from 2009 to 2015. The United Kingdom consistently demonstrates a substantially higher volume of growth events compared to France and Germany, with annual figures ranging from approximately 430 to 550 events. This dominance suggests a more active or mature market for high-growth exits in the UK during the observed period. In contrast, France and Germany report significantly fewer growth events, with France generally recording between 90 and 130 events per cohort and Germany showing a declining trend from about 160 events in 2009 to fewer than 80 by 2015. Notably, Germany starts the period with more growth events than France but is overtaken from 2011 onward, as French growth events remain relatively stable or slightly increase, while German figures steadily decline. These patterns indicate that, during this timeframe, the UK ecosystem offered more frequent opportunities for rapid firm scaling and exit,

whereas France exhibited stable but moderate growth event rates, and Germany experienced a contraction in such outcomes. This divergence may reflect differences in market size, investor activity, regulatory environments, or the maturity of entrepreneurial ecosystems across these countries.

Figure 2: Growth Events by Country and Year (2009-2023)



Notes:

### 4.3 Predictive Models of Entrepreneurial Quality

We combine our business registry data with data from the Moody's Orbis and Zephyr databases to estimate three logit regression models to examine how the presence or absence of a startup characteristic predicts the probability of growth in UK, France, and Germany. The dependent variable *Growth* is a dummy variable equal to 1 if a firm achieves an IPO or is acquired within 6 years of registration, as reported in Moody's Zephyr database. *Patent* is equal to 1 if a firm holds a patent within the first year and 0 otherwise. *Short Name* is a dummy variable that equals 1 if the firm's name is in the 10th percentile based on the total number of characters in its length. *Eponimiy* is a variable that equals 1 if the firm's name contains one of the 1,000 most common personal names in the respective country<sup>3</sup>. We also include two dummy variables to identify private and public limited liability companies (*Private Ltd. Company* and *Public Ltd. Company*, respectively). We

<sup>3</sup>Name frequencies are calculated using person with significant control (UK & Germany) and names of individual entrepreneurs in the register (France).

finally consider the industry within which the firm is operating, by including industry dummies based on the Eurostat NACE industry classification<sup>4</sup>.

Table 2 reports our results for the predictive models for all firms registered in the three selected countries before 2016 (2,712,757 firm in the UK, 1,153,832 firms in France and 1,212,940 firms in Germany). The results and the explanatory power of the models (*Pseudo R*<sup>2</sup>) are broadly consistent with those of (Guzman and Stern, 2020). Specifically, the presence of patents and the incorporation of a public limited company are associated with a higher likelihood of a growth outcome. Conversely, if the firm’s name contains common personal names, it is negatively associated with entrepreneurial growth. The key difference with respect to (Guzman and Stern, 2020) is the lack of positive predictive power associated with having a short name.

Table 2: Predictive Analytics Model of Growth

	<i>Dependent variable: Growth</i>		
	UK	FR	GER
Patents	2.546*** (0.104)	2.218*** (0.195)	2.482*** (0.077)
Short Name	−0.066 (0.059)	−0.433*** (0.147)	0.012 (0.080)
Eponymy	−0.170** (0.068)	−0.401* (0.209)	−1.110*** (0.123)
Private Ltd. Company	1.546*** (0.322)	1.710*** (0.086)	
Public Ltd. Company	6.168*** (0.328)	3.377*** (0.231)	2.364*** (0.112)
Constant	−7.409*** (0.327)	−6.789*** (0.168)	−11.425*** (1.001)
Industry Dummies	YES	YES	YES
Observations	2,712,757	1,153,832	1,212,940
Pseudo <i>R</i> <sup>2</sup>	0.128	0.145	0.114
Chi <sup>2</sup>	5758.290	1891.652	2223.035

*Notes:* Significance levels: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ . Robust standard errors in parentheses. The predictive growth model is a logit regression where Growth is a binary variable equal to 1 if a firm achieves IPO or acquisition within 6 years, and 0 otherwise. Growth is defined for firms born before 2016.

#### 4.4 Predictive Quality and Robustness

To assess the robustness and predictive quality of our entrepreneurial quality model, we conduct a tenfold cross-validation procedure using firm-level data from each country. Cross-validation is a standard technique in predictive modeling that involves partitioning the data into subsets, or “folds,” repeatedly training the model on a portion of the data while testing it on the remaining fold. This process is repeated ten times, ensuring that each data point is used both for training and

<sup>4</sup>For the UK we use UK SIC code 2007, which is identical to the NACE classification until the fourth digit level.

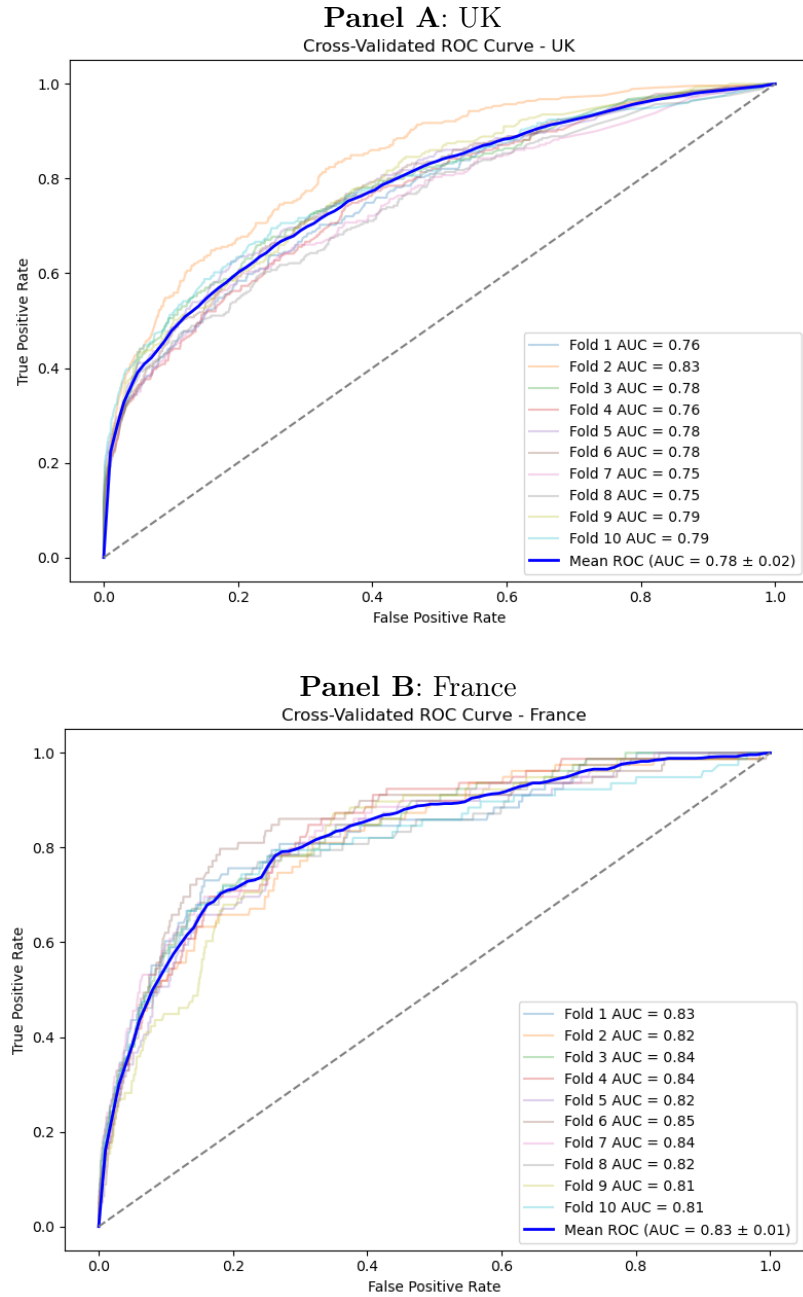
validation. The goal is to estimate how well the model generalizes to unseen data, thus providing a robust measure of out-of-sample performance.

To evaluate the accuracy of our predictions, we compute Receiver Operating Characteristic (ROC) curves and their associated Area Under the Curve (AUC) values. The ROC curve plots the true positive rate (sensitivity) against the false positive rate ( $1 - \text{specificity}$ ) at various threshold settings. It provides a visual representation of the model’s ability to discriminate between positive and negative outcomes—in our case, whether a newly founded firm is likely to become high-growth.

The AUC value summarizes the ROC curve in a single number between 0 and 1. A model with an AUC of 0.5 performs no better than random guessing, while an AUC of 1.0 represents perfect classification. In practical terms, an AUC above 0.7 is typically considered acceptable, above 0.8 is good, and above 0.9 is excellent. As shown in Figure 3, Panels A and B display the ROC curves for the United Kingdom and France, respectively. Both models exhibit strong predictive performance, with AUC values indicating that our model reliably distinguishes high-growth firms at the time of founding based on observable characteristics.

These validation results give confidence in the robustness of our quality estimation methodology. They also support the use of our model to produce meaningful region-level measures of entrepreneurial quality that can inform the cross-regional and cross-country comparisons presented in the remainder of the analysis.

Figure 3: Out-of-Sample ROC Curves



Notes:

## 5 The State of European Entrepreneurship

Table 3 presents summary statistics for the sample of region-year observations across France, the UK, and Germany. The mean number of firm registrations (Firm Quantity) is substantially higher in France (2,012) and the UK (2,557) compared to Germany (207), reflecting the finer spatial granularity of the German NUTS 3 regions. In contrast, quality-adjusted entrepreneurial activity (RECPI) is highest in the UK (mean = 2.88), followed by France (1.86), and significantly lower in Germany (0.22), suggesting differences in both the scale and growth potential of new ventures. Across countries, the EQI—our firm-level quality index—displays a low variance, with similar means around 0.001, reflecting its normalization across the population of new firms.

Table 3: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
<b>Panel A: France</b>								
Firm Quantity	1,400	2,012.266	3,055.752	102	544.5	1,100	2,055.2	37,110
Firm Quality (EQI)	1,400	0.001	0.0003	0.0002	0.001	0.001	0.001	0.002
Quality Adjusted-Quantity (RECPI)	1,400	1.855	4.483	0.026	0.326	0.680	1.605	63.424
GDP per capita	1,400	28,569.410	11,784.030	14,300	23,501.5	26,000	30,300	123,385
Population Density	1,400	549.519	2,388.394	2.707	49.613	83.798	167.146	21,399.090
Nb. Higher Education Graduates	1,100	0.003	0.005	0.000	0.000	0.000	0.004	0.032
Nb. VC Deals (3 Years)	1,300	0.017	0.039	0.000	0.004	0.009	0.017	0.602
Rural Area	1,400	0.530	0.499	0	0	1	1	1
Distance to Nearest Urban Area (km)	1,400	228.760	756.984	0.000	58.915	99.651	138.957	4,602.481
Border Region	1,400	0.220	0.414	0	0	0	0	1
<b>Panel B: UK</b>								
Firm Quantity	1,947	2,557.016	2,656.644	31	949.5	1,749	3,269.5	23,157
Firm Quality (EQI)	1,947	0.001	0.0003	0.0004	0.001	0.001	0.001	0.007
Quality Adjusted-Quantity (RECPI)	1,947	2.880	3.863	0.036	0.943	1.789	3.473	48.074
GDP per capita	1,947	35,520.040	44,075.480	14,694	24,134	28,568	35,222.5	576,383
Population Density	1,947	1,763.266	2,636.959	6.793	214.126	550.026	2,255.915	15,339.000
Nb. Higher Education Graduates	1,768	0.010	0.020	0.000	0.000	0.001	0.015	0.192
Nb. VC Deals (3 Years)	1,945	0.052	0.355	0.000	0.005	0.013	0.028	7.651
Rural Area	1,947	0.102	0.302	0	0	0	0	1
Distance to Nearest Urban Area (km)	1,947	19.927	47.455	0.000	0.000	0.000	29.906	417.442
Border Region	1,947	0.028	0.166	0	0	0	0	1
<b>Panel C: Germany</b>								
Firm Quantity	5,600	206.954	513.884	9	68	115	197	10,289
Firm Quality (EQI)	5,600	0.001	0.0004	0.0003	0.001	0.001	0.001	0.006
Quality Adjusted-Quantity (RECPI)	5,600	0.215	0.611	0.005	0.059	0.107	0.196	10.899
GDP per capita	5,600	35,230.400	15,916.030	12,100	25,735.2	31,300	39,200	196,000
Population Density	5,600	525.724	688.741	35.442	115.310	197.574	667.305	4,823.473
Nb. Higher Education Graduates	4,400	0.004	0.008	0.000	0.000	0.000	0.005	0.062
Nb. VC Deals (3 Years)	5,200	0.008	0.018	0.000	0.000	0.000	0.009	0.221
Rural Area	5,600	0.272	0.445	0	0	0	1	1
Distance to Nearest Urban Area (km)	5,600	44.488	36.770	0.000	14.894	40.227	66.341	153.899
Border Region	5,600	0.158	0.364	0	0	0	0	1

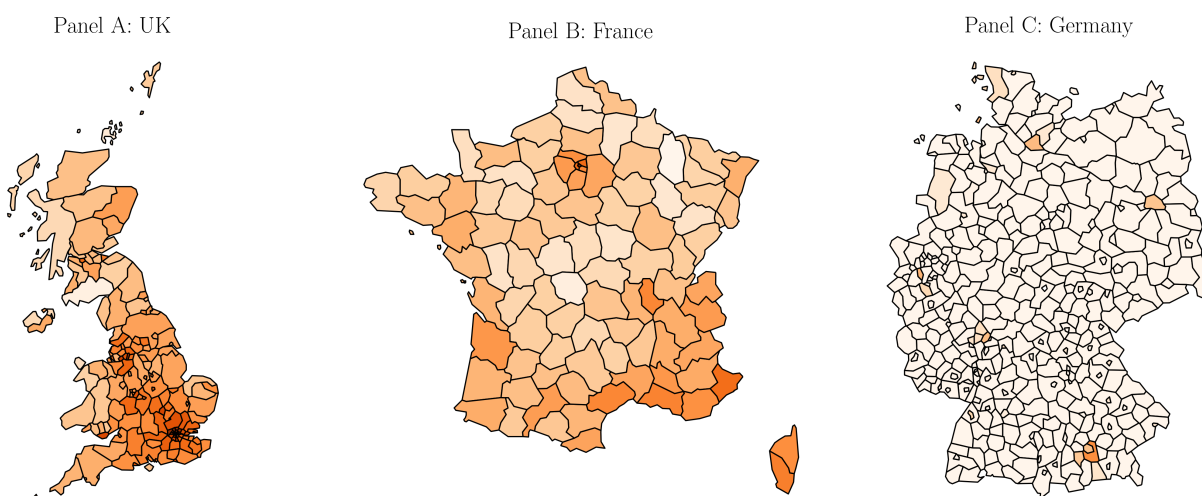
Notes: Summary statistics for the sample used in the regression, where each observation represents a region-year.

Economic and demographic variables show considerable heterogeneity. The UK and Germany

exhibit higher average GDP per capita than France, but with larger standard deviations, particularly in the UK due to extreme values. Population density also varies widely, with the UK showing the highest mean and dispersion. Measures of human capital (higher education graduates) and access to financial capital (venture capital deals) are generally low in magnitude and highly skewed, consistent with the concentration of such resources in a small number of regions.

The rural-urban composition differs markedly across countries: 53% of the French region-year observations are classified as rural, compared to 27% in Germany and just 10% in the UK. Correspondingly, average distance to the nearest urban area is much higher in France (229 km), reflecting its more dispersed geography, whereas urban proximity is generally close in the UK and Germany. Lastly, the share of border regions varies from 22% in France to 16% in Germany and 3% in the UK, suggesting differing regional contexts for cross-border entrepreneurial dynamics.

Figure 4: Startup Formation per capita



*Notes:*

Figure 4 shows in Panels A, B, and C the geographic distribution of startup formation per population across the United Kingdom, France, and Germany, respectively. In the United Kingdom (Panel A), startup activity is heavily concentrated in the southern and southeastern regions, particularly around London and its surrounding counties, as indicated by the darkest shading. There is also notable activity in metropolitan areas such as Manchester and Birmingham, with a gradual decrease in startup formation as one moves towards the northern and more rural regions.

In France (Panel B), the highest density of startup formation is observed in the Île-de-France region, which includes Paris, as well as in the southeastern departments such as Rhône-Alpes and Provence-Alpes-Côte d'Azur. These regions are shaded most intensely, reflecting their status as major economic and innovation hubs. Other areas, particularly in the central and northern parts of the country, exhibit moderate to low levels of startup activity.

Germany (Panel C) displays a markedly different pattern, with startup formation highly localized

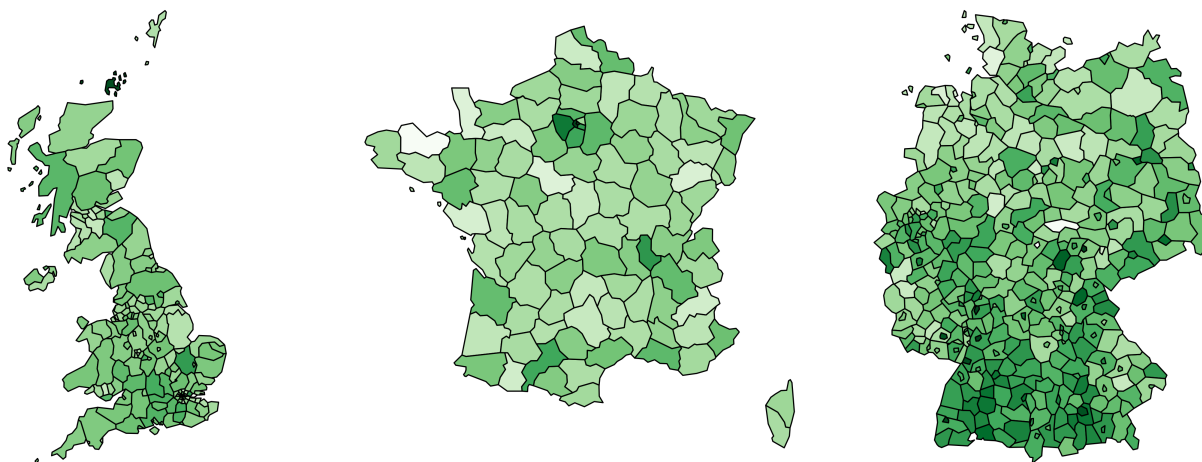


to a few urban centers. The most prominent concentrations are seen in Berlin, Munich, and the Frankfurt am Main area, with very limited activity elsewhere, as shown by the light shading across most regions. This suggests that, relative to the UK and France, Germany’s startup ecosystem is more geographically concentrated and less dispersed.

Overall, the maps highlight significant regional disparities in startup formation within each country, with the UK and France exhibiting broader regional participation—albeit with clear metropolitan dominance—while Germany’s startup activity is largely confined to a small number of major cities. These patterns likely reflect differences in regional economic development, infrastructure, access to capital, and policy environments.

Figure 5 presents choropleth maps of the United Kingdom, France, and Germany, illustrating the regional distribution of the Entrepreneurial Quality Index (EQI), a metric designed to capture the growth potential of new firms based on observable characteristics at or soon after firm founding. Darker shades indicate regions with higher average EQI, signifying a greater likelihood that startups in those areas will achieve significant growth outcomes such as acquisition, merger, or initial public offering.

Figure 5: EQI



*Notes:*

In the United Kingdom, the highest EQI values are concentrated in and around London and its southeastern environs, with additional pockets of elevated entrepreneurial quality in other major urban centers such as Manchester and Edinburgh. This pattern suggests that the growth potential of startups is strongly linked to metropolitan regions with established innovation ecosystems and access to resources.

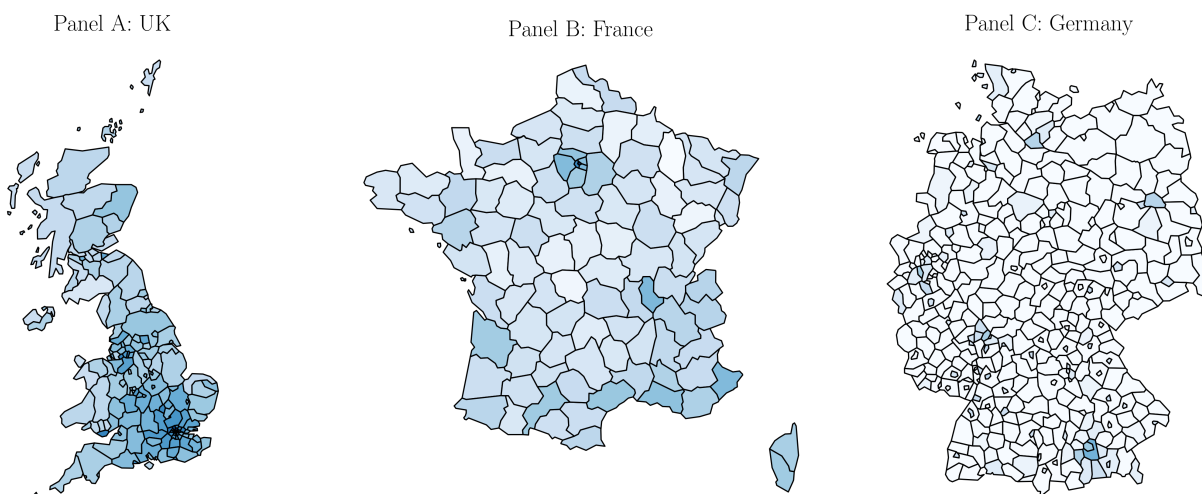
For France, the Île-de-France region (encompassing Paris) stands out with the darkest shading, indicating a pronounced concentration of high-quality entrepreneurial activity. Other regions with relatively high EQI include Rhône-Alpes and Provence-Alpes-Côte d’Azur, while much of the

country exhibits moderate to low EQI values, highlighting the persistent dominance of Paris as the nation’s entrepreneurial hub.

In Germany, the distribution of EQI is more geographically dispersed but still reveals clear hotspots, particularly around Berlin, Munich, and the Frankfurt am Main area. Southern Germany, notably Bavaria and Baden-Württemberg, also displays higher EQI values, reflecting the region’s strong industrial and technological base. However, large areas of eastern and northern Germany show lighter shading, indicating lower average entrepreneurial quality.

Overall, the maps reveal that regions with higher EQI, and thus greater startup growth potential, tend to cluster around major urban and economic centers in all three countries. This spatial concentration of entrepreneurial quality underscores the importance of local ecosystems, infrastructure, and access to talent and capital in fostering high-growth startups. The observed geographic disparities also suggest that policies aimed at enhancing regional entrepreneurial quality could play a critical role in balancing economic development and innovation across broader national territories.

Figure 6: RECPI per capita



*Notes:*

Figure 6 presents choropleth maps of the United Kingdom, France, and Germany that illustrate the per capita values of the Regional Entrepreneurship Cohort Potential Index (RECPI), a quality-adjusted measure of entrepreneurial activity capturing the density of high-potential startups relative to the local population. The maps reveal distinct spatial patterns across countries. In the UK (Panel A), elevated RECPI per capita values appear not only in major metropolitan areas but also in select rural regions such as West Norfolk (UKH17), Monmouthshire and Newport (UKL14), and Shropshire (UKG11), suggesting the presence of localized enablers of high-quality entrepreneurship outside core urban centers. France (Panel B) exhibits a more geographically dispersed distribution of per capita startup potential, with several rural departments—such as Ain (FRK21), Charente-Maritime (FRI32), and Morbihan (FRH04)—showing unexpectedly high val-

ues, often tied to sectoral strengths like maritime activities and tourism. In Germany (Panel C), high RECPI per capita values are similarly spread across both urban and non-urban regions, with standout cases including Göttingen (DE949), home to a major research university, and Schleswig-Flensburg (DEF07), a peripheral but dynamic border region.

While rural areas generally display lower RECPI values compared to intermediate and urban regions, these notable exceptions highlight the role of local ecosystem dynamics. Factors such as proximity to innovation hubs, the presence of universities, or specialized industry clusters can contribute to strong entrepreneurial outcomes even in sparsely populated areas. These findings underscore the importance of adopting an ecosystem-based perspective when evaluating regional entrepreneurship, recognizing that high-potential activity can emerge from diverse and context-specific combinations of economic, institutional, and geographic conditions.

## 6 The Role of Entrepreneurial Ecosystems

Table 4 presents the results from estimating the fixed-effects OLS regression model described in Equation 4. The dependent variable Quantity represents the total number of startups created in a region within a given year for each country, while Quality corresponds to the region’s RECPI as a measure of quality-adjusted entrepreneurial activity. The analysis covers the period 2009–2023 for France and Germany and 2010–2020 for the UK. All specifications include region (NUTS 3) and year fixed effects, with standard errors clustered at the region level. Each covariate is interacted with a dummy variable identifying rural areas based on the Eurostat Rural-Urban Typology. These results serve as a preliminary exploration of the association between regional covariates of interest and entrepreneurial activity across the three countries.

Columns (1) and (2) present the results for the French sample. In France, traditional factors commonly associated with high-potential entrepreneurship in non-rural areas—such as GDP per capita, population density, and access to venture capital—exhibit significant correlations with entrepreneurial activity, particularly with quality-adjusted entrepreneurship. However, the coefficients of the interaction terms are of similar magnitude but opposite in sign to the non-interacted coefficients, suggesting that these associations largely vanish in rural areas. This discrepancy implies that no single factor alone can explain entrepreneurial success in rural regions. Instead, it may indicate complementarity between these factors. From an entrepreneurial ecosystem perspective, multiple interconnected factors—such as regional economic performance, access to education, and access to financial capital jointly contribute to fostering entrepreneurship and the lack of those in rural areas could explain the lack of significance.

Columns (3) and (4) report estimates for the UK, where the results are qualitatively similar to those observed in France, except for population density and venture capital deals in rural areas. However, the estimates for the UK are generally less statistically significant. Columns (5) and (6) correspond to Germany. While some point estimates align with expected signs, the coefficients are not statistically significant.

Table 4: Main Results: Fixed Effects Estimation

	<i>Dependent variable:</i>					
	France		UK		Germany	
	$\log(\text{Quantity}_t)$	Quality <sub>t</sub>	$\log(\text{Quantity}_t)$	Quality <sub>t</sub>	$\log(\text{Quantity}_t)$	Quality <sub>t</sub>
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{GDP per capita}_{t-1})$	0.375*** (0.143)	12.627*** (4.535)	0.153 (0.151)	0.194 (0.582)	0.182* (0.101)	0.042 (0.035)
$\log(\text{GDP per capita}_{t-1}) \times \text{Rural}$	-0.050 (0.141)	-15.757*** (4.426)	-0.156 (0.120)	-0.806** (0.310)	-0.135 (0.093)	0.022 (0.023)
Population density <sub>t-1</sub>	0.00003 (0.00004)	-0.013 (0.009)	-0.0002*** (0.0001)	0.002*** (0.001)	0.00000 (0.0001)	0.0004 (0.0003)
Population density <sub>t-1</sub> $\times$ Rural	0.014*** (0.004)	0.077*** (0.018)	0.025 (0.020)	0.037 (0.026)	0.001 (0.001)	-0.0003 (0.0002)
$\log(\text{Graduates HEI}_{t-1} + 1)$	-1.910** (0.787)	44.877** (19.538)	-6.260** (2.930)	-61.370 (38.160)	-0.292 (2.835)	0.812 (1.326)
$\log(\text{Graduates HEI}_{t-1} + 1) \times \text{Rural}$	1.736 (1.827)	-35.664** (14.642)	24.332** (12.000)	101.629* (51.627)	-0.526 (11.158)	0.931 (1.742)
$\log(\text{VC deals (3 Years)}_{t-1} + 1)$	0.039 (0.167)	49.426*** (11.632)	0.245 (0.190)	10.856*** (2.493)	0.142 (0.407)	0.160 (0.573)
$\log(\text{VC deals (3 Years)}_{t-1} + 1) \times \text{Rural}$	0.211 (0.767)	-39.043*** (11.307)	-0.286 (1.104)	-12.029*** (3.421)	-0.649 (0.909)	-0.304 (0.554)
Region (NUTS 3) Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1,100	1,100	1,593	1,593	4,400	4,400
R <sup>2</sup>	0.997	0.966	0.989	0.962	0.972	0.991
Adjusted R <sup>2</sup>	0.996	0.961	0.988	0.957	0.969	0.990

*Notes:* This table presents estimates from OLS regressions based on the models described in Equation 4. The dependent variable Quantity represents the total number of startups created in a region within a given year for each country, while Quality refers to each region RECPI (quality-adjusted entrepreneurial activity index). Columns (1) and (2) report baseline results for the French subsample, Columns (3) and (4) present estimates for the UK, and Columns (5) and (6) correspond to Germany. The timeframe covered is 2009–2023 for France and Germany, and 2010–2020 for the UK. All specifications include region (NUTS 3) and year fixed effects. Standard errors are clustered at the NUTS 3 level. Significance levels: \* p<0.1; \*\* p<0.05; \*\*\* p<0.01.

There are important factors to consider when interpreting the results for the UK and Germany. In the UK, the number of rural regions is relatively small (18), and rural entrepreneurial activity is minimal according to our data. In Germany, the high level of regional disaggregation - comprising over 400 NUTS 3 regions - may contribute to the lack of statistical significance. This greater granularity could result in limited variation in the dependent variables, as many regions exhibit very little fluctuation in the outcomes we are measuring. This argument can be generalized at some extent to both France and UK, as the high R<sup>2</sup> indicates that there is little variance left to be explain in this fixed effect model.

Table 5 presents the main results from pooled OLS regressions for France, the UK, and Germany, with two dependent variables: the logarithm of the total number of startups created in a region (Quantity) and the regional entrepreneurial quality index (RECPI, denoted as Quality). Several patterns emerge, pointing to substantial cross-country heterogeneity in the determinants of entrepreneurial activity.

GDP per capita, is strongly associated with startup quantity in France and Germany, but not in the UK. In contrast, GDP per capita significantly predicts startup quality in the UK, suggesting

Table 5: Main Results: Pooled OLS

	<i>Dependent variable:</i>					
	France		UK		Germany	
	$\log(\text{Quantity}_t)$	Quality <sub>t</sub>	$\log(\text{Quantity}_t)$	Quality <sub>t</sub>	$\log(\text{Quantity}_t)$	Quality <sub>t</sub>
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{GDP per capita}_{t-1})$	1.099*** (0.350)	-0.754 (1.011)	0.277 (0.173)	2.586*** (0.832)	0.853*** (0.095)	0.170 (0.107)
Rural	-0.835*** (0.103)	-0.806*** (0.226)	-1.392*** (0.216)	-1.362*** (0.381)	-0.463*** (0.052)	-0.017 (0.023)
$\log(\text{Area})$	0.125 (0.131)	0.389 (0.248)	0.431*** (0.057)	1.116*** (0.213)	0.670*** (0.030)	0.280*** (0.054)
Population density <sub>t-1</sub>	0.0001* (0.00004)	0.001*** (0.0001)	0.0002*** (0.00003)	0.001*** (0.0002)	0.001*** (0.0001)	0.001*** (0.0002)
Graduates HEI <sub>t-1</sub>	4.992 (6.230)	41.238 (34.784)	6.788** (3.057)	32.206** (13.711)	5.329 (4.583)	-12.742** (5.103)
VC deals (3 Years) <sub>t-1</sub>	-1.074 (1.507)	59.851*** (4.141)	-0.013 (0.076)	4.276*** (0.685)	4.562*** (1.256)	14.366*** (5.371)
$\log(\text{Dist. Urban} + 1)$	-0.171*** (0.036)	-0.372*** (0.114)	-0.185*** (0.036)	-0.310*** (0.092)	-0.147*** (0.017)	0.011 (0.018)
Border Region	-0.164 (0.109)	-0.161 (0.190)	-0.145 (0.362)	-0.209 (0.566)	0.020 (0.060)	-0.022 (0.020)
Costal Region Type 1	0.589*** (0.089)	0.352* (0.206)	-0.360*** (0.095)	-0.582* (0.335)	0.191** (0.076)	0.084 (0.096)
Costal Region Type 2			0.197* (0.116)	0.979** (0.445)	0.332*** (0.115)	0.096** (0.048)
NUTS 3 Fixed Effects	NO	NO	NO	NO	NO	NO
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	1,100	1,100	1,593	1,593	4,400	4,400
R <sup>2</sup>	0.821	0.912	0.672	0.746	0.756	0.602
Adjusted R <sup>2</sup>	0.818	0.911	0.668	0.743	0.754	0.601

*Notes:* This table presents estimates from OLS regressions based on the models described in Equation 4. The dependent variable Quantity represents the total number of startups created in a region within a given year for each country, while Quality refers to each region RECPI (quality-adjusted entrepreneurial activity index). Columns (1) and (2) report baseline results for the French subsample, Columns (3) and (4) present estimates for the UK, and Columns (5) and (6) correspond to Germany. The timeframe covered is 2009–2023 for France and Germany, and 2010–2020 for the UK. All specifications include region (NUTS 3) and year fixed effects. Standard errors are clustered at the NUTS 3 level. Significance levels: \* p<0.1; \*\* p<0.05; \*\*\* p<0.01.

that higher-income regions there may specialize in high-growth or innovation-intensive ventures. The lack of a corresponding quality effect in France and Germany might reflect a broader distribution of entrepreneurial outcomes across income levels, or structural differences in the geography of innovation.

Rural regions consistently show significantly lower levels of both startup quantity and quality across countries, with the strongest penalties observed in the UK. However, the rural dummy is not significant for startup quality in Germany, suggesting that rural areas in Germany may still foster high-quality entrepreneurial activity. This aligns with Germany’s relatively decentralized economic structure and the presence of strong regional industrial bases outside major urban hubs.

Spatial and demographic characteristics also matter. Larger area size is positively associated with entrepreneurial activity, particularly in Germany and the UK, where both the number and quality of startups increase with regional size. Population density exerts a uniformly positive effect on both dimensions of entrepreneurship across all countries, underscoring the role of agglomeration economies in fostering vibrant startup ecosystems.

Human capital, proxied by the number of higher education institution (HEI) graduates, plays a differentiated role. It is a significant driver of both startup quantity and quality in the UK, but not in France or Germany. Surprisingly, in Germany, HEI graduates are negatively associated with startup quality. One possible explanation is that highly educated individuals in Germany may preferentially enter established firms or academia, or they may relocate to larger urban centers, thus weakening the local link between education and high-quality entrepreneurship.

The availability of venture capital (VC) deals is a strong and consistent predictor of startup quality across all three countries. The magnitude of the coefficient is particularly large in France, suggesting that VC access may be a key lever for enhancing entrepreneurial quality. In Germany, VC also significantly affects startup quantity, reinforcing the link between financial capital and entrepreneurial dynamism.

Proximity to urban centers, measured through the log distance to the nearest urban area, is negatively associated with both startup quantity and quality, especially in France and the UK. This is consistent with the view that urban areas provide richer entrepreneurial ecosystems, including access to markets, talent, and infrastructure. In Germany, only startup quantity is significantly affected by urban proximity, again reflecting the potential for high-quality entrepreneurship to occur outside urban cores.

Finally, regional typologies based on geographical location reveal nuanced patterns. Coastal regions (Type 1) are positively associated with startup quantity in France and Germany but negatively associated in the UK, where both startup quantity and quality are significantly lower in these areas. Conversely, Coastal Type 2 regions (potentially representing more peripheral coastal zones) show positive and significant associations with entrepreneurial outcomes in the UK and Germany. Border regions, however, do not exhibit significant effects in any specification.

Overall, these results highlight both commonalities and national specificities in the drivers of entrepreneurial quantity and quality. While population density and venture capital availability

emerge as universal positive factors, the effects of GDP per capita, human capital, and spatial geography vary significantly across countries, reflecting institutional, cultural, and economic differences in regional entrepreneurial ecosystems.

The caveats underscore the importance of accounting for the structural differences across countries when evaluating the factors influencing rural entrepreneurial activity. Moreover, the choice of geographical unit of analysis significantly affects the results and comparisons, highlighting the need to select an analytical level that accurately reflects entrepreneurial activity in a way that allows for meaningful comparisons across these countries. While ecosystem perspectives are essential, data limitations in certain regions may lead to divergent conclusions that warrant further exploration.

## 7 Conclusion

This study provides insights into the role of regional factors in shaping entrepreneurial outcomes (quantity and quality of entrepreneurship) across the three largest European economies (UK, France, and Germany). Preliminary findings presented in this paper reveal that while some factors—such as population density and venture capital availability—consistently correlate with entrepreneurial outcomes across France, the UK, and Germany, their effects vary substantially depending on geography and national context. Rural regions, in particular, face systemic disadvantages, with weaker associations between traditional entrepreneurship drivers and both the quantity and quality of startups. The fixed-effects regressions for France and the UK show that in rural areas, the positive effects of GDP per capita, human capital, and access to venture capital observed in urban regions tend to vanish. This suggests the presence of complementarities among ecosystem components, where the absence of one element—such as financial capital or market access—can undermine the effectiveness of others. Germany’s results, while less statistically robust, point to the unique structure of its regional economy, where certain rural areas may still support quality entrepreneurship, likely due to their industrial base or decentralized innovation infrastructure.

These results emphasize the need for a place-based policy approach tailored to the specific entrepreneurial dynamics of rural regions. Broad, one-size-fits-all interventions are unlikely to address the multifaceted constraints these regions face. Instead, policies that foster local entrepreneurial ecosystems through integrated support for education, finance, and infrastructure may prove more effective. Moreover, methodological considerations—such as the high fixed-effects  $R^2$  and the impact of regional disaggregation in Germany—highlight the importance of choosing appropriate spatial scales and accounting for structural differences across countries. Future research should build on these insights by leveraging richer microdata, exploring causal mechanisms, and assessing the role of policy interventions in shaping entrepreneurial activity in rural and peripheral regions.



## References

- Acs, Z. and C. Armington (2004). “Employment Growth and Entrepreneurial Activity in Cities.” *Regional Studies* 38(8), 911–927. (Visited on 02/10/2025).
- Andrews, R., C. Fazio, J. Guzman, Y. Liu, and S. Stern (2022). “The Startup Cartography Project: Measuring and mapping entrepreneurial ecosystems.” *Research Policy* 51(2), 104437. (Visited on 05/26/2025).
- Audretsch, D. B., M. Belitski, and N. Cherkas (2021). “Entrepreneurial ecosystems in cities: The role of institutions.” *PLOS ONE* 16(3), e0247609. (Visited on 02/10/2025).
- Content, J., N. Bosma, J. Jordaan, and M. Sanders (2020). “Entrepreneurial ecosystems, entrepreneurial activity and economic growth: new evidence from European regions.” *Regional Studies* 54(8), 1007–1019. (Visited on 02/10/2025).
- Feldman, M. P. (2001). “The Entrepreneurial Event Revisited: Firm Formation in a Regional Context.” *Industrial and Corporate Change* 10(4), 861–891. (Visited on 05/26/2025).
- Glaeser, E. L., S. P. Kerr, and W. R. Kerr (2015). “Entrepreneurship and Urban Growth: An Empirical Assessment with Historical Mines.” *The Review of Economics and Statistics* 97(2), 498–520. (Visited on 02/10/2025).
- Glaeser, E. L., W. R. Kerr, and G. A. M. Ponzetto (2010). “Clusters of entrepreneurship.” *Journal of Urban Economics* 67(1), 150–168. (Visited on 05/26/2025).
- Guzman, J. and S. Stern (2020). “The State of American Entrepreneurship: New Estimates of the Quantity and Quality of Entrepreneurship for 32 US States, 1988–2014.” *American Economic Journal: Economic Policy* 12(4), 212–243. (Visited on 09/10/2024).
- Kortum, S. and J. Lerner (2000). “Assessing the Contribution of Venture Capital to Innovation.” *The RAND Journal of Economics* 31(4), 674–692. (Visited on 05/26/2025).
- Lerner, J. (2009). “The Empirical Impact of Intellectual Property Rights on Innovation: Puzzles and Clues.” *American Economic Review* 99(2), 343–348. (Visited on 05/26/2025).
- Samila, S. and O. Sorenson (2011). “Venture Capital, Entrepreneurship, and Economic Growth.” *The Review of Economics and Statistics* 93(1), 338–349. (Visited on 05/26/2025).
- Stam, E. (2015). “Entrepreneurial Ecosystems and Regional Policy: A Sympathetic Critique.” *European Planning Studies* 23(9), 1759–1769. (Visited on 05/26/2025).
- Stam, E. and A. Van De Ven (2021). “Entrepreneurial ecosystem elements.” *Small Business Economics* 56(2), 809–832. (Visited on 09/10/2024).
- Tartari, V. and S. Stern (2021). *More than an Ivory Tower: The Impact of Research Institutions on the Quantity and Quality of Entrepreneurship*. w28846. Cambridge, MA: National Bureau of Economic Research, w28846. DOI: [10.3386/w28846](https://doi.org/10.3386/w28846). URL: <http://www.nber.org/papers/w28846.pdf> (visited on 09/10/2024).