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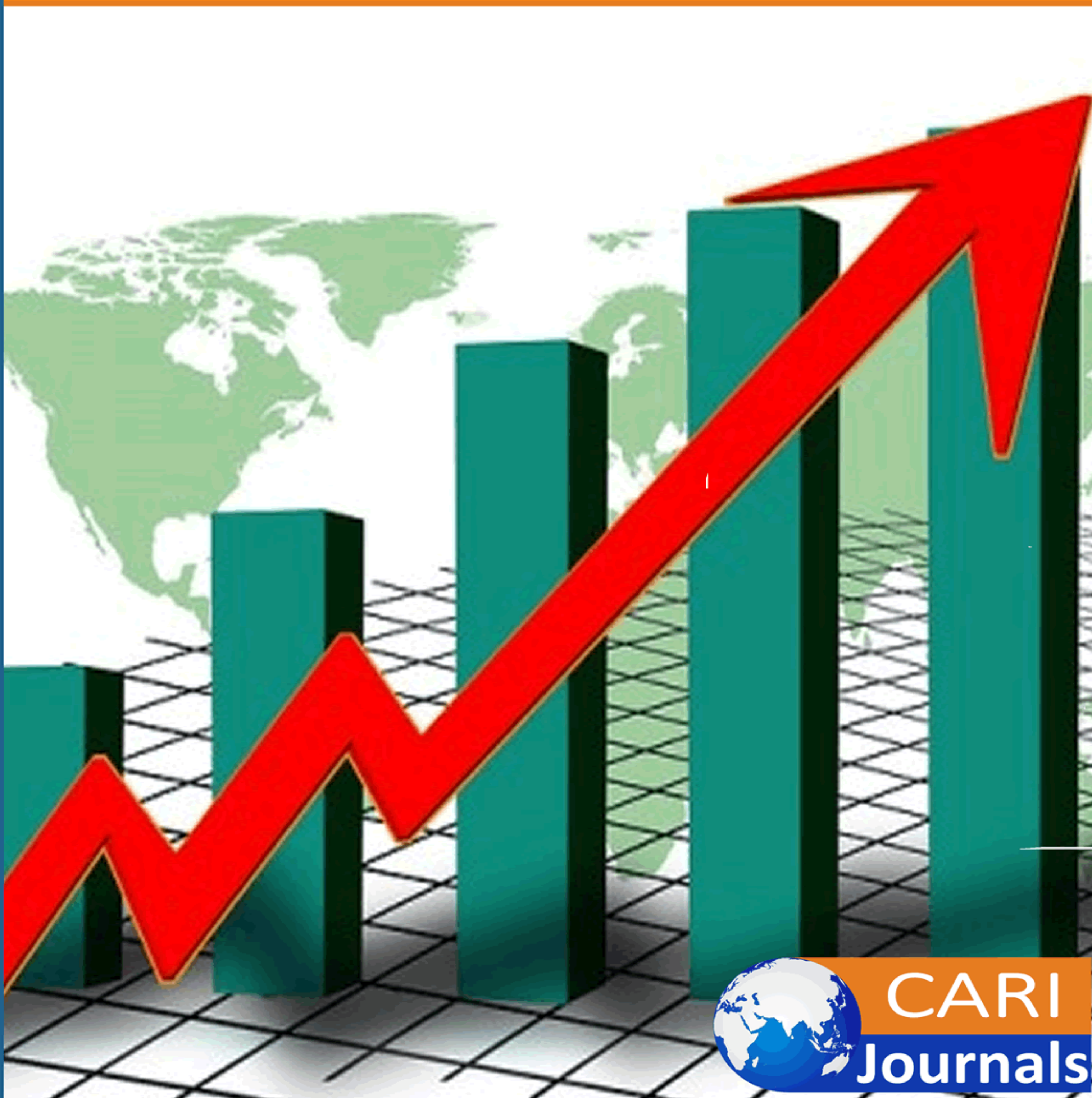

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Beyond Geographical Localization: Individual Determinants of Knowledge Spillover Absorption in Inventors

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Abstract

Purpose: This paper examines how individual-level characteristics shape inventors' ability to absorb knowledge spillovers. While prior research has focused on firm- or regional-level determinants, this study investigates the micro-foundations of spillover absorption by analyzing how education, experience breadth, and mobility jointly influence knowledge diffusion.

Methodology: Using inventor-level data from the PatVal-EU survey covering 6,327 inventors in six European countries, a series of binary probit models estimates the probability of absorbing near and distant knowledge spillovers. Three hypotheses are tested on the influence of labor mobility, knowledge breadth, and depth on knowledge spillover absorption. Six model specifications separately and jointly assess these effects.

Findings: Results show that inter-regional mobility significantly increases the probability of absorbing knowledge spillovers, while intra-regional or residential mobility has a limited influence. Education depth positively affects spillover absorption up to the Master's level, but PhD education yields no additional benefit, suggesting diminishing returns to knowledge depth. The Herfindahl Index of experience concentration is negative and significant, indicating that broader technological experience enhances absorptive ability. Contrary to the hypothesized inverted-U pattern, knowledge breadth positively linearly affects spillover absorption. The results confirm that mobility and absorptive capacity complement each other, helping individuals internalize knowledge from geographically

Unique Contribution to Theory, Practice and Policy: The study extends absorptive capacity theory to the individual level, demonstrating that education, cognitive diversity, and mobility jointly determine spillover absorption. It contributes to innovation policy and practice by emphasizing the benefits of promoting inter-regional mobility and the importance of both depth and breadth of knowledge.

Keywords: *Knowledge Spillovers, Absorptive Capacity, Labor Mobility, Innovation, Knowledge Breadth and Depth*

JEL Codes: *O31, O33, J24, J61, R11*

1. INTRODUCTION

Knowledge spillovers are central to the process of innovation and economic growth. As ideas circulate beyond organizational and regional boundaries, they generate positive externalities that sustain technological advancement and regional development. Traditionally, the literature has emphasized geographical proximity as the key driver of spillovers, arguing that face-to-face interaction and shared labor markets foster the exchange of tacit knowledge (Jaffe et al. 1993). Firms and research institutions co-locate within industrial clusters to exploit these localized exchanges, reinforcing the view that innovation thrives in dense, interactive environments.

However, such spatial explanations overlook the variation in how individuals actually absorb and transmit external knowledge. Theories of absorptive capacity (Cohen & Levinthal, 1990) suggest that personal characteristics—such as prior learning, education, and experience diversity—shape one's ability to recognize, assimilate, and apply new information. Thus, the significance of this topic lies in understanding how knowledge spillovers are not only geographically mediated but also cognitively and institutionally determined. As globalization, digitalization, and cross-border labor flows redefine the landscape of innovation, examining the intersection of spatial and individual factors becomes increasingly vital for both theory and policy.

This study investigates how individual-level heterogeneity, captured through labor mobility and absorptive capacity, influences the likelihood of knowledge spillovers being absorbed and transmitted. Using inventor-level data from the PatVal-EU survey, which covers over 6,000 patents across six European countries, the analysis integrates classical and contemporary perspectives on knowledge diffusion. Specifically, it tests three hypotheses: (H_1) whether labor mobility enhances spillover absorption; (H_2) whether knowledge breadth exhibits an inverted U-shaped relationship with spillovers; and (H_3) whether knowledge depth positively affects spillover absorption. By employing probit models that directly measure near and distant knowledge flows, this research moves beyond citation-based proxies to capture the micro-level mechanisms of learning.

In doing so, it contributes to a nuanced understanding of how geography, cognition, and institutional context interact to shape innovation systems. The study's insights not only refine the theory of absorptive capacity at the individual level but also highlight policy implications for promoting mobility, interdisciplinary education, and openness in regional innovation ecosystems.

2. KNOWLEDGE SPILLOVER, LOCALIZATION, AND INDIVIDUAL HETEROGENEITY

Knowledge is often regarded as a public good with positive externalities (Nelson, 1959; Arrow, 1962). Due to its tacit and non-excludable nature, knowledge usually spills over across individuals and organizations. The literature indicates that physical proximity fosters spillovers by facilitating information exchange and interaction (Audretsch et al., 2025; Giuri & Mariani, 2013). Consequently, firms, research institutes, and universities co-locate within clusters that become the stem of innovation (Marx et al., 2015). Thus, geographical proximity is a critical condition for knowledge spillover, particularly through face-to-face contact and shared labor markets (Jaffe, Trajtenberg, & Henderson, 1993).

But not all actors equally benefit from these localized exchanges. Cohen & Levinthal (1990) have shown that the capacity to recognize, assimilate, and apply external knowledge shapes who is able to benefit from spillovers. The literature has argued that prior knowledge and diverse experience strengthen learning as they enhance the individual's ability to organize new information (Aguiar & Gagnepain, 2022; Bower & Hilgard, 1981). Similarly, individuals with greater educational depth and experiential breadth develop a stronger absorptive capacity. Therefore, the relationship between physical proximity and knowledge depends on individual heterogeneity, especially in absorptive capacity and learning ability.

Labor mobility has been widely recognized as a key mechanism where knowledge spillovers occur. Various regional and cross-national studies have highlighted how the movement of skilled individuals allows for ideas and technological insight (Di Addario et al., 2025). Almeida and Kogut (1999) found that engineers frequently cite patents from prior employers. This demonstrates that mobility enables the transfer of knowledge in career transition. Furthermore, Song et al. (2001) found international mobility among Korean and Taiwanese semiconductor engineers accelerated cross-border knowledge diffusion. More recently, Akerman and Holzeuh (2025) argue, by using firm-level micro data, worker mobility is an important source of firm productivity growth. This suggests that human movement bridges regional innovation systems.

Koike-Mori et al. (2023) and Agrawal et al. (2006) argued that knowledge spillover goes beyond spatial movement as social ties amplify these effects. According to the study, enduring personal relationships maintain the flow of knowledge even after individuals relocate across firms or regions. Similarly, Fleming et al. (2007) emphasized collaborative brokerage, showing that moving individuals serve as bridges between disconnected groups. Particularly, the knowledge spillover effect is shown to be particularly significant in the recent big-tech context (Sun & Kejriwal, 2023).

However, mobility is not only a channel of spillovers, but is shaped by policy and institutional environments. Marx et al. (2015) explain that institutional constraints limit mobility as a channel. The study demonstrated that non-compete agreements weaken spillover. This contrasts with the open labor markets of Silicon Valley, where knowledge flows freely through job mobility. Thus, labor mobility is shaped by surrounding policy and the institutional environment. So individuals who experience job transitions often exhibit greater absorptive capacity. This prompts this study to test the following hypothesis:

H1: Labor mobility increases the likelihood of absorbing and transmitting knowledge spillovers.

Moreover, the diversity of prior knowledge strongly shapes how individuals and organizations

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absorb external ideas. A broader knowledge base often expands cognitive repertoire, which helps individuals in combining insights creatively (Li & Zheng, 2025). This is because diverse experiences enhance memory structure (Nie *et al.,* 2022; Bower and Hilgard, 1981) and moderate cognitive diversity within an alliance, fostering innovation (Wuyts et al., 2005).

But these benefits of knowledge diversity are limited. Nooteboom (2000) argued that excessive heterogeneity creates cognitive distance. This gap bounds communication and shared understanding. Similarly, Lane et al. (2006) showed that excessive diversity fragments meaning systems, which weaken knowledge integration. Thus, at high levels, diversity constrains rather than enhances absorptive capacity.

Thus, spillovers are maximized when inventors have a balanced knowledge portfolio. One that is broad enough to recognize diverse opportunities, but not so scattered that integration becomes complex. Empirical works suggest a curvilinear relationship as breadth maximizes spillovers, but very high breadth decreases absorbative capacity in individuals (Laursen & Salter, 2006). The curvilinear relationship suggests the following hypothesis:

H2: Knowledge breadth follows an inverted U-shaped relationship with knowledge spillovers.

Furthermore, the depth of expertise plays a critical role when shaping how individual firms absorb external knowledge. Based on the absorptive capacity theory, accumulated and domain-specific knowledge enhances one's ability to recognize and apply new information. Cohen and Levinthal (1990) suggest that prior related knowledge creates the cognitive structures needed to identify valuable external insights, and Lane et al. (2006) and Nie et al. (2022) emphasize that absorptive capacity is cumulative and deepened through sustained specialization. These factors strengthen the efficiency and selectivity of knowledge absorption because individuals will evaluate external ideas with more precision.

Empirical studies confirm this effect. Giuri and Mariana (2013) highlighted that higher education levels correlate with inventors' tendency to draw on science and technical knowledge sources in patenting. So, deeper expertise allows for efficient knowledge transition. Similarly, Zucker and Darby (2007) show that R&D collaborations from highly specialized scientists achieve greater innovation productivity because of the superior assimilation of external knowledge input.

Depth also exhibits diminishing returns, particularly at high levels of specialization. Fleming et al. (2007) proved that at high levels of specialization, the marginal benefits of depth plateau as search and recombination capacity decline. Thus, knowledge depth provides a positive foundation for spillover as it complements the curvilinear effects of breadth. The positive foundation emphasizes this hypothesis:

H3: Knowledge depth positively influences knowledge spillovers.

Traditional literature emphasizes the importance of physical proximity when facilitating knowledge spillovers. However, Autio et al. (2018) have highlighted how new technological and institutional developments reshape how knowledge diffuses. Digital platforms, such as online research networks and virtual scientific communities, enable interaction without spatial constraints. This reduces reliance on co-location. Similarly, open innovation practices shift spillover dynamics from being accidental to being strategic (Chesbrough, 2003; Laursen & Salter, 2006). Moreover, globalization expands these channels as international migration and global R&D alliances expand spillover channels beyond local ecosystems (Branstetter, 2006).

These studies emphasize that geography is no longer the sole determinant of spillover dynamics. Instead, individual heterogeneity based on mobility, knowledge breadth, and depth plays critical roles in knowledge spillover. Therefore, this study will integrate both classical spatial and emerging digital-global perspectives to test how personal characteristics complement geographical proximity when explaining the mechanisms of knowledge spillovers.

Together, these developments highlight that geography is no longer the sole determinant of spillover dynamics. Instead, individual heterogeneity based on mobility, knowledge breadth, and depth plays a crucial role in mediating access to and absorption of external knowledge. This study, therefore, integrates both classical spatial and emerging digital-global perspectives, testing how personal characteristics complement geographical proximity in explaining the mechanisms of knowledge spillovers.

3. METHODOLOGY

3.1 Data Variables

This study examines how individual-level heterogeneity, as captured by absorptive capacity and labor mobility, influences inventors' ability to absorb knowledge spillovers. The analysis is based on the PatVal-EU survey dataset, which contains detailed information on patents granted by the European Patent Office (EPO) between 1993 and 1998. The dataset includes inventor-level survey responses for 9,550 patents across six European countries. [1] After data cleaning and removal of missing observations, 6,327 inventor-level records were retained for the analysis.

The dependent variables measure whether the focal inventor benefited from knowledge spillovers during the inventive process. Following the survey question asking inventors to evaluate the importance of interactions with people located within or beyond one hour of travel, two dummy variables were constructed. Near Knowledge Spillover (*CE_dummy2*) equals 1 if local interaction was used and 0 otherwise. Similarly, Far Knowledge Spillover (*DE_dummy2*) equals 1 if interaction with distant collaborators was used and 0 otherwise. These binary measures capture whether the inventor absorbed local or distant spillovers, offering a more direct indicator than citation-based proxies. Although many previous studies use patent citation data to trace the flow of knowledge, their measurement accuracy is limited because citations are typically entered by

[1] The dataset used in this study was originally compiled by Giuri and Mariani (2013) for their paper "When Distance Disappears: Inventors, Education, and the Locus of Knowledge Spillovers," *Review of Economics and Statistics,* 95*(2), 449–463.*

patent examiners rather than by inventors (Harhoff et al., 2009). Therefore, direct interview data are more suitable for examining whether inventors absorb knowledge spillovers during the inventive process.

In the meantime, absorptive capacity was measured through two dimensions. The first, depth of knowledge, was proxied by education variables. University or Master's Degree (*UniMasDegree*) was coded 1 if the inventor's highest degree is BA/MA and 0 otherwise. Similarly, PhD Degree (*PhDDegree*) equals 1 if the highest degree is PhD and 0 otherwise. Measuring absorptive capacity along two dimensions are widely accepted in the recent literature of absorptive capacity (Huang et al., 2022).

In a robustness specification, these were replaced with an ordered variable, Education Depth (*education_depth*), with 0 for no university degree, 1 for BA/MA, and 2 for Ph.D. For an additional comparison, a restricted-sample model is used with a categorical variable, Education Level (*education.level*), which equals 1 for Ph.D. and 0 for BA/MA inventors. The purpose of this restricted-sample model is to test whether PhD training provides a greater absorptive advantage than BA/MA training.

The second proxy of absorptive capacity, breadth of knowledge, was measured by the Herfindahl Index of experience (*herfinv1*), which measures concentration across technological classes of the inventor's prior patents. A lower value implies broader experience. To capture potential nonlinearity, a squared term (I($herfinv1^2$)) was included in one model to test for an inverted-U relationship between breadth and spillovers.

Labor mobility was represented by three variables. Mobility Out Region (*reg_mob_nuts3Out*) was coded 1 if the inventor changed both employer and NUTS-3 region during the previous ten years and 0 otherwise. Mobility In Region (*reg_mob_nuts3In*) equals 1 if the inventor changed employers within the same region and 0 otherwise. Finally, Residence Degree (*residence_degree*) was coded 1 if the country from which the focal inventor earned the degree is different than the country where the focal patent has been invented, and 0 otherwise. These variables capture the extent to which inventors' spatial and occupational mobility contribute to the delocalization of knowledge flows.

Control variables include demographic characteristics (*Age*, *Male*, *year_first_patent*), patent features (S*K_ScLit*, *Ninventors*), applicant-type dummies (*Firm_Applic*, *PRI_Applic*, *Individual_Applic*), patent motivations (*reasonCommExploit*, *reasonLic*, *reasonImit*), and regional characteristics (*lgdppop_nuts3*, *lpop_nuts3*, *larea_nuts3_km2*).

Detailed descriptions of the variables are provided in Table 1, and descriptive statistics for all variables are reported in Table 2.

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3.2 Model Specification and Estimation Strategy

Because the dependent variables, *Near* and *Far knowledge spillover*, are dichotomous, a binary probit model was employed to estimate the probability that inventor *i* benefits from knowledge spillovers:

$$P(Y_i = 1) = \Phi(X_i'\beta)$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution, and X_i represents the vector of explanatory and control variables. The probit specification assumes the latent propensity to absorb spillovers follows a normal distribution, which is suitable for modeling the unobserved continuous likelihood of spillover absorption (Verbeek, 2008).

Table 1. Data and Variable Construction

Category	Variable	Description / Measurement
Dependent Variables	*CE_dummy2*	1 = Inventor reports local (within one-hour distance) spillover interactions; 0 otherwise.
	DE_dummy2	1 = Inventor reports distant (beyond one-hour distance) spillover interactions; 0 otherwise.
Education / Knowledge Depth	*UniMasDegree*	1 = Bachelor's or Master's degree, 0 otherwise.
	PhDDegree	1 = Ph.D. degree, 0 otherwise.
	education_depth	Ordered variable: 0 = below university, 1 = BA/MA, 2 = PhD.
	education.level	Dummy variable (PhD = 1, BA/MA = 0) for restricted sample.
Knowledge Breadth	*herfinv1*	Inverse Herfindahl Index of technological experience concentration across IPC classes. Lower value = broader experience.
	I(herfinv1²)	Squared term of Herfindahl Index for nonlinearity (inverted-U test).
Labor Mobility	*reg_mob_nuts3In*	1 = Changed employer within the same NUTS-3 region.
	reg_mob_nuts3Out	1 = Changed employer and NUTS-3 region.
	residence_degree	1 = Changed residential location.
Demographics and Career	*Age*	Inventor's age at the time of patent application.
	Male	1 = Male inventor.
	year_first_patent	Year inventor's first patent was filed.
Patent Features	*SK_ScLit*	Importance of scientific literature for invention (scale 0–5).
	Ninventors	Number of inventors per patent.

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Category	Variable	Description / Measurement
Applicant Type	*Firm_Applic*	1 = Patent owned by firm.
	PRI_Applic	1 = Patent owned by public research institution.
	Individual_Applic	1 = Patent owned by individual applicant.
Patent Motivation	*reasonCommExploit*	Importance of commercial exploitation (scale 1–5).
	reasonLic	Importance of licensing motivation (scale 1–5).
	reasonImit	Importance of preventing imitation (scale 1–5).
Regional Controls	*lgdppop_nuts3*	Log of GDP per capita at regional level (NUTS-3).
	lpop_nuts3	Log of regional population.
	larea_nuts3_km2	Log of regional area (km²).

To explore how mobility and absorptive capacity jointly or separately influence spillovers, six specifications were estimated (Table 3). The *Mobility Near* and *Far* models include only mobility variables (without absorptive capacity) and controls. These models assess whether regional and job mobility increases the likelihood of absorbing local (*CE_dummy2*) or distant (*DE_dummy2*) spillovers (H_1). The *Absorptive Capacity Far* model with nonlinear knowledge breadth term (squared HHI) tests the relationship between education depth (education_depth) and knowledge breadth (*herfinv1*, *herfinv1²*). A significant negative squared term would support an inverted-U relationship between experience diversity and spillovers (H_2).

Table 2. Descriptive Statistics (Numerical and Categorical Variables)

Variable	Description (Variable Name)	Mean	SD	Min	Max	N (0) (%)	N (1) (%)
Continuous Variables							
Knowledge Breadth (Herfindahl Index, *herfinv1*)	Inverse of experience concentration	0.52	0.41	0.00	1.00	—	—
Scientific Literature Importance (*SK_ScLit*)	Relevance of scientific literature for patent	2.63	1.86	0.00	5.00	—	—
Age (*Age*)	Age of inventor	44.85	9.66	20.00	79.00	—	—
Year of First Patent (*year_first_patent*)	Year inventor filed first patent	1995.8	8.2	1975	2014	—	—
Number of Inventors (*Ninventors*)	Team size per patent	2.36	1.50	1.00	15.00	—	—
GDP per capita (*lgdppop_nuts3*)	Log GDP per capita	10.38	0.34	9.56	11.24	—	—
Population (*lpop_nuts3*)	Log population of region	12.11	0.83	10.24	14.11	—	—

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Variable	Description (Variable Name)	Mean	SD	Min	Max	N (0) (%)	N (1) (%)
Area (*larea_nuts3_km2*)	Log regional area (km²)	8.06	0.49	6.80	9.34	—	—
Commercial Exploitation Importance (*reasonCommExploit*)	Patent motivated by commercial use	3.48	1.30	1	5	—	—
Licensing Importance (*reasonLic*)	Patent motivated by licensing	2.56	1.34	1	5	—	—
Prevent Imitation (*reasonImit*)	Patent motivated by imitation prevention	3.78	1.17	1	5	—	—
Categorical Variables							
Near Knowledge Spillover (*CE_dummy2*)	1 = Near knowledge spillover	—	—	—	—	4 390 (69.23 %)	1 951 (30.77 %)
Far Knowledge Spillover (*DE_dummy2*)	1 = Far knowledge spillover	—	—	—	—	3 726 (58.76 %)	2 615 (41.24 %)
Male (*Male*)	1 = Male inventor	—	—	—	—	155 (2.44 %)	6 186 (97.56 %)
University or Master's Degree (*UniMasDegree*)	1 = BA/MA degree	—	—	—	—	1 974 (31.18 %)	4 353 (68.82 %)
PhD Degree (*PhDDegree*)	1 = PhD	—	—	—	—	5 558 (87.84 %)	769 (12.16 %)
Mobility In Region (*reg_mob_nuts3In*)	1 = Moved within NUTS3 region	—	—	—	—	4 927 (77.90 %)	1 400 (22.10 %)
Mobility Out Region (*reg_mob_nuts3Out*)	1 = Moved outside NUTS3 region	—	—	—	—	4 502 (71.10 %)	1 825 (28.90 %)
Residence Degree (*residence_degree*)	1 = Changed residence	—	—	—	—	2 270 (35.90 %)	4 057 (64.10 %)
Firm Applicant (*Firm_Applic*)	1 = Firm applicant	—	—	—	—	2 661 (42.10 %)	3 666 (57.90 %)
Public Research Institution (*PRI_Applic*)	1 = Public research institution applicant	—	—	—	—	5 757 (90.97 %)	570 (9.03 %)

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Variable	**Description (Variable Name)**	**Mean**	**SD**	**Min**	**Max**	**N (0) (%)**	**N (1) (%)**
Individual Applicant (*Individual_Applic*)	1 = Individual applicant	—	—	—	—	4 225 (66.80 %)	2 102 (33.20 %)

The *Absorptive Capacity Far* model without the nonlinear knowledge breadth term (squared HHI) replaces the ordered education variable with separate *UniMasDegree* and *PhDDegree* dummies and only includes linear knowledge breadth (*herfinv)* to confirm the effects of knowledge depth (BA/MA and PhD) compared to a high school degree. The *Full* model combines mobility and absorptive-capacity variables to examine their joint influence on knowledge diffusion (H_1–H_3). Finally, the *Education Level* model restricts the sample to university-educated inventors (Low_High_School = 0) and codes education level as 1 for PhD and 0 for BA/MA to isolate the incremental impact of doctoral education.

Each model was estimated using maximum likelihood. Standard errors are reported in parentheses, and significance levels are indicated as $p < 0.10$, $p < 0.05$, and $p < 0.01$. Marginal effects, rather than raw coefficients, are presented in Table 3 to indicate the change in the probability of absorbing knowledge spillovers for a one-unit change in each independent variable, keeping other variables constant. This facilitates interpretation in probabilistic terms.

4. FINDINGS

This section presents the empirical results from six probit estimations examining the impact of labor mobility and absorptive capacity on the probability of absorbing knowledge spillovers. All marginal effects are presented in Table 3.

The *Mobility Near* and *Far* models (the first and second columns of Table 3) focus exclusively on the role of labor mobility. The coefficient for *Mobility Out Region* **(***reg_mob_nuts3Out***)** is positive and significant in both the near-spillover model ($\beta = 0.086$, $p = 0.043$) and the far-spillover model ($\beta = 0.099$, $p = 0.017$). This suggests that inventors who switch employers and regions are significantly more likely to absorb both local and, especially, distant knowledge spillovers. The effect is more substantial for far spillovers, suggesting that inter-regional mobility expands inventors' access to non-local knowledge sources and thereby facilitates delocalization of knowledge.

The *Mobility In Region* ***(***reg_mob_nuts3In***)*** coefficient is positive but only marginally significant for near spillovers ($p \approx 0.08$), while residential mobility (*residence_degree*) shows no significant association.

These findings support H_1, confirming that labor mobility, particularly inter-regional, acts as a conduit for knowledge diffusion across geographical boundaries. Local job changes alone do not significantly increase the probability of spillover absorption, indicating that spatial relocation is more important than organizational switching within the same region.

The *Absorptive Capacity Far* model with a nonlinear knowledge breadth term (squared HHI) (the third column of Table 3) tests how absorptive capacity, measured by education depth (*education_depth*) and knowledge breadth (*herfinv1*), affects distant spillover absorption. The coefficient for education depth is positive and statistically significant ($\beta = 0.097$, $p < 0.001$), indicating that higher educational attainment enhances inventors' ability to internalize external knowledge. However, knowledge breadth **(***herfinv1***)** and its squared term (*herfinv1²*) are statistically insignificant ($p = 0.81$ and $p = 0.38$, respectively), suggesting no strong evidence for an inverted-U pattern in the relationship between experience diversity and spillover absorption.

This result partially supports H_2. While the depth of education plays a significant role in increasing absorptive capacity, knowledge breadth may not exhibit the hypothesized inverted-U relationship with spillover absorption. Among the controls, Age exhibits a consistently negative effect ($p < 0.001$), implying that younger inventors are more open to learning from external sources. Scientific Literature Importance **(***SK_ScLit***)** remains highly significant ($p < 0.001$), underscoring that inventors drawing on scientific knowledge are more likely to benefit from external spillovers.

The *Absorptive Capacity Far* model without the nonlinear knowledge breadth term (squared HHI) (the fourth column of Table 3) tests whether absorptive capacity gains plateau beyond the Master's level while also considering the role of knowledge breadth. Both University/Master's Degree **(***UniMasDegree***)** and PhD Degree **(***PhDDegree***)** show positive and highly significant coefficients for far spillovers ($\beta = 0.153, p < 0.001; \beta = 0.208, p < 0.001$). This result confirms that higher education levels increase the probability of absorbing distant knowledge spillovers. However, the modest difference in magnitude between these two coefficients implies that the positive impact of education depth may plateau at some point**.** This provides a nuanced support for H_3: while a higher education level can increase spillover absorption of inventors, this positive effect of education can have diminishing returns.

Turning to knowledge breadth, the coefficient of the Herfindahl Index **(***herfinv1***)** is negative and significant ($\beta = -0.131, p = 0.002$). Because a higher HHI indicates greater concentration (less diversity), the negative sign implies that inventors with broader technological experience, those who have worked across a wider set of technology classes, are more likely to absorb knowledge spillovers. In other words, knowledge breadth has a positive linear relationship with spillover absorption.

This finding partially supports H_2**,** but in a linear rather than nonlinear form. The inclusion of the squared Herfindahl term (*herfinv1²*) in the previous model shows no significant result ($p = 0.38$), indicating that the hypothesized inverted-U pattern does not hold empirically. Instead, the

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result from the current model suggests that knowledge diversity continuously enhances absorptive performance, without reaching a saturation point.

As in earlier models, Age remains negatively significant (*$p < 0.001$*), and Scientific Literature Importance **(***SK_ScLit***)** continues to display a strong positive association (*$p < 0.001$*), indicating that younger inventors and those drawing on scientific knowledge are more effective at leveraging external ideas.

The *Full* model (the fifth column of Table 3) combines the mobility and absorptive-capacity dimensions to assess their joint effects on spillover absorption. The results reveal that Mobility Out Region **(***reg_mob_nuts3Out***)** maintains a significant positive influence ($\beta = 0.089, p = 0.032$), underscoring the importance of inter-regional job changes for accessing new knowledge environments. Among the absorptive-capacity variables, both *UniMasDegree* ($\beta = 0.154, p < 0.001$) and *PhDDegree* ($\beta = 0.203, p < 0.001$) remain significant, confirming the robustness of the education–spillover relationship. Meanwhile, the Herfindahl Index **(***herfinv1***)** again shows a negative and significant coefficient ($p = 0.002$), meaning that inventors with broader, more diversified technological backgrounds are more capable of absorbing external knowledge**.** Overall, this result demonstrates that mobility and knowledge diversity complement each other: inter-regional mobility exposes inventors to new ideas, and technological breadth equips them to internalize those ideas effectively. Education continues to strengthen this process by enhancing cognitive absorptive capacity.

The *Education Level* model (the sixth column of Table 3) restricts the analysis to inventors with at least a Bachelor's degree to assess whether PhD training adds an incremental benefit. The coefficient for education level (*education.level***)** is positive but statistically insignificant ($\beta = 0.059, p = 0.15$), indicating that PhD holders are not significantly more likely than BA/MA inventors to absorb distant spillovers.

This result reinforces the threshold interpretation of educational effects implied in the *Absorptive Capacity* model: absorptive capacity increases with formal education up to a certain level but does not continue to rise with further academic specialization. In this restricted sample, Herfindahl Index **(***herfinv1***)** remains negative and highly significant **(**$\beta = –0.179, p < 0.001$**)**, again showing that knowledge breadth—rather than specialization—enhances spillover absorption**.** Similarly, Mobility Out Region **(***reg_mob_nuts3Out***)** continues to exert a positive and significant influence ($p = 0.018$), confirming the critical role of spatial mobility in facilitating knowledge diffusion across regional boundaries.

Scientific Literature Importance **(***SK_ScLit***)** remains strongly significant ($p < 0.001$), further indicating that scientific engagement complements experiential and spatial openness in boosting absorptive performance.

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Table 3. Bivariate Probit Estimation: Marginal Effect on Probability

Variables	1. Mobility		Absorptive Capacity		3. Full Model	4. Education Level
	Near	Far	Far with HHI²	Far without HHI²	Far without HHI²	Far with higher education sample
Education Depth (education_depth)	—	—	0.097*** (0.027)	—	—	—
University or Master's Degree (UniMasDegree)	—	—	—	0.153*** (0.046)	0.154*** (0.046)	—
PhD Degree (PhDDegree)	—	—	—	0.208*** (0.055)	0.203*** (0.055)	—
Education Level (education.level)	—	—	—	—	—	0.059 (0.041)
Knowledge Breadth (herfinv1)	—	—	0.050 (0.209)	-0.130** (0.042)	-0.130** (0.042)	-0.179*** (0.047)
Knowledge Breadth² (herfinv1²)	—	—	-0.171 (0.193)	—	—	—
Mobility In Region (reg_mob_nuts3In)	0.121* (0.069)	0.088 (0.067)	—	—	0.097 (0.067)	0.074 (0.077)
Mobility Out Region (reg_mob_nuts3Out)	0.086** (0.043)	0.099** (0.041)	—	—	0.089* (0.041)	0.107** (0.045)
Residence Degree (residence_degree)	-0.109 (0.089)	-0.042 (0.084)	—	—	-0.053 (0.084)	-0.081 (0.090)
Age (Age)	-0.010*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
Male (Male)	0.152 (0.111)	0.114 (0.106)	0.114 (0.106)	0.114 (0.106)	0.114 (0.106)	0.236** (0.118)
Year of First Patent (year_first_patent)	-0.002 (0.003)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	-0.004 (0.004)

Scientific Literature Importance (SK_ScLit)	0.072*** (0.010)	0.081*** (0.009)	0.081*** (0.009)	0.081*** (0.009)	0.081*** (0.009)	0.069*** (0.011)
Firm Applicant (Firm_Applic)	-0.532 (0.403)	-0.064 (0.386)	-0.064 (0.386)	-0.064 (0.386)	-0.064 (0.386)	-0.442 (0.428)
Public Research Institution (PRI_Applic)	-0.505 (0.413)	0.040 (0.396)	0.040 (0.396)	0.040 (0.396)	0.040 (0.396)	0.043 (0.398)
Individual Applicant (Individual_Applic)	-0.571 (0.408)	-0.206 (0.390)	-0.206 (0.390)	-0.206 (0.390)	-0.206 (0.390)	-0.211 (0.391)
Number of Inventors (Ninventors)	-0.015 (0.012)	-0.008 (0.011)	-0.008 (0.011)	-0.008 (0.011)	-0.008 (0.011)	-0.008 (0.011)
Commercial Exploitation (reasonCommExploit)	0.018 (0.011)	0.020* (0.011)	0.020* (0.011)	0.020* (0.011)	0.020* (0.011)	0.020* (0.011)
Licensing (reasonLic)	0.075*** (0.011)	0.064*** (0.011)	0.064*** (0.011)	0.064*** (0.011)	0.064*** (0.011)	0.064*** (0.011)
Prevent Imitation (reasonImit)	0.025** (0.011)	0.015 (0.011)	0.015 (0.011)	0.015 (0.011)	0.015 (0.011)	0.015 (0.011)
Log GDP per Capita (lgdppop_nuts3)	-0.290*** (0.061)	-0.337*** (0.059)	-0.337*** (0.059)	-0.337*** (0.059)	-0.337*** (0.059)	-0.337*** (0.059)
Log Population (lpop_nuts3)	0.010 (0.023)	-0.029 (0.022)	-0.029 (0.022)	-0.029 (0.022)	-0.029 (0.022)	-0.029 (0.022)
Log Area (larea_nuts3_km2)	-0.115*** (0.019)	-0.077*** (0.019)	-0.077*** (0.019)	-0.077*** (0.019)	-0.077*** (0.019)	-0.077*** (0.019)
Intercept	6.645 (6.976)	-5.154 (8.686)	-5.154 (8.686)	-5.154 (8.686)	-5.154 (8.686)	11.141 (8.347)
N	6,327	6,327	6,327	6,327	6,327	5,137

Note: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

5. DISCUSSION

The findings confirm that labor mobility serves as a key mechanism for knowledge diffusion, particularly across organizational and regional boundaries. The positive coefficient for Mobility

Out Region ($p < 0.05$) indicates that inter-regional moves expose inventors to diverse, non-local knowledge bases, validating the view that individuals act as "carriers of tacit knowledge" (Almeida & Kogut, 1999; Song et al., 2001, Di Addario et al., 2025).

This result aligns with Cohen and Levinthal's (1990) theory of absorptive capacity, where prior related knowledge enhances a firm's ability to recognize and apply external information. By moving between firms or regions, inventors expand the cognitive domain of their new environment, enabling the recombination of distinct knowledge sets. Such exchanges help bridge cognitive distance while maintaining sufficient proximity for mutual understanding (Nooteboom, 2000).

Institutional conditions further shape this process. Marx, Singh, and Fleming (2015) show that freer labor markets strengthen knowledge spillovers, while restrictive regimes, such as those enforcing non-competes, limit diffusion. Hence, environments that encourage inventor mobility promote cross-fertilization of ideas and cumulative learning (Marx et al., 2009). Recently, Khlystova & Kalyuzhnova (2025) found that in resource-rich countries, where overreliance on resources can hinder innovation, knowledge spillover shows further significance in shaping innovation and development. It reinforces that implication that institution conditions the extent, mechanism, and impact of knowledge spillover.

At a systemic level, this reflects Laursen and Salter's (2006) concept of openness: broad external search improves innovative performance up to an optimal threshold. Similarly, regional openness to mobility fosters variety and recombination but must balance stability and flexibility (Nooteboom, 2000). Overall, labor mobility enhances innovation by expanding absorptive capacity and enabling the interactive learning that underpins knowledge-based growth.

Building on the preceding evidence that labor mobility facilitates knowledge diffusion, the results further reveal that the breadth of individual knowledge enhances the capacity to absorb spillovers. The negative and significant coefficient of the Herfindahl Index indicates that inventors with more diversified technological experience are better positioned to internalize and recombine external knowledge. This finding supports cognitive diversity theories (Bower & Hilgard, 1981; Wuyts et al., 2005), which emphasize that exposure to varied domains strengthens associative learning and enables creative problem-solving.

Unlike organizational-level studies that identify diminishing returns to openness, the absence of a significant squared term suggests a monotonically positive effect of diversity within the observed range. This challenges Nooteboom's (2000) "cognitive distance" constraint, which posits an optimal balance between novelty and understandability. At the individual level, inventors appear able to manage higher levels of diversity without suffering from integration overload—likely because their cognitive flexibility allows them to bridge heterogeneous knowledge domains more effectively than organizations can.

This distinction echoes Laursen and Salter's (2006) curvilinear model of openness, where excessive external search becomes counterproductive at the firm level. Here, however, individual inventors operate below that saturation threshold, using diverse experiences to amplify their absorptive capacity (Cohen & Levinthal, 1990). Overall, the findings suggest that breadth fosters adaptability, enabling inventors to connect previously unlinked technological trajectories and thereby strengthen the micro-foundations of inter-firm knowledge spillovers.

Extending the analysis of cognitive breadth, the findings demonstrate that educational depth also plays a critical role in shaping absorptive capacity. The strong significance of both UniMasDegree and PhDDegree ($p < 0.001$) confirms that higher formal education enhances an inventor's ability to recognize, assimilate, and apply external knowledge, consistent with Cohen and Levinthal's (1990) foundational model and the extended framework of Lane, Koka, and Pathak (2006). Advanced education equips individuals with broader analytical schemas and refined problem-solving heuristics that facilitate the transformation of external inputs into innovative outcomes.

However, the non-significant difference between PhD and BA/MA levels ($p = 0.15$) indicates that returns to education diminish beyond a certain threshold. This pattern reflects the "over-specialization" constraint identified by Fleming, Mingo, and Chen (2007), where excessive disciplinary focus narrows exploratory behavior and limits cross-domain recombination. Similarly, Giuri and Mariani (2013) found that while education strengthens engagement with scientific knowledge, it does not indefinitely increase sensitivity to external spillovers.

These results refine absorptive capacity theory by suggesting that formal education enhances learning only up to a cognitive ceiling, after which further gains depend more on experiential mechanisms such as knowledge diversity and mobility. In combination, these findings portray absorptive capacity as multi-dimensional: formal education builds the foundation for learning, but continuous exposure to diverse and dynamic contexts sustains it. This bridges the micro-level cognition of inventors with the broader system of inter-organizational knowledge flows.

Overall, the results indicate that mobility and absorptive capacity operate as complementary mechanisms of spillover absorption. Mobility broadens inventors' exposure to diverse knowledge environments, while education and experience diversity determine their ability to internalize and apply new ideas. This mirrors Boschma's (2005) dual-mechanism framework, where proximity enables interaction and cognitive diversity ensures effective assimilation. In this sense, mobility functions as the spatial catalyst of contact, whereas absorptive traits define the depth of learning derived from it.

The interaction also supports insights from the learning-by-hiring literature (Song et al., 2001; Rosenkopf & Almeida, 2003), which stresses that both who moves and what they know shape the quality of knowledge flows. Inventors with broader experience and higher education contribute not only by transferring ideas but by transforming them, which integraties their prior expertise into

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new technological contexts. This dynamic refines Nooteboom's (2000) view of learning by interaction, suggesting that cognitive diversity enables individuals to bridge distant knowledge domains without the coordination barriers often faced by organizations.

Furthermore, the significant effects of Age ($p < 0.001$) and SK_ScLit ($p < 0.001$) show that younger inventors and those engaged with scientific literature are more receptive to external knowledge. This aligns with Zucker and Darby (2007), who highlight the vital role of scientifically trained individuals in sustaining innovation spillovers.

Together, these findings reveal that knowledge diffusion is maximized when exposure, absorptive capacity, and receptivity intersect. Mobility opens access to external ideas, education and diversity enable their assimilation, and scientific engagement keeps learning cumulative: forming a synergistic engine of technological renewal.

Building on these integrative insights, the findings point to several implications for innovation and human capital policy. Since inter-regional mobility emerged as a key mechanism of spillover diffusion, policies that lower mobility barriers could substantially enhance cross-cluster learning. Encouraging inventors to move between geographically and institutionally diverse environments facilitates the circulation of tacit knowledge, reinforcing what Marx et al. (2009) and Branstetter (2006) identified as the pivotal role of mobility in sustaining bidirectional knowledge flows.

At the same time, education policy should be designed for absorptive learning rather than specialization alone. The results indicate that spillover benefits peak at the undergraduate and Master's levels, where applied and interdisciplinary exposure broadens cognitive frameworks. Public funding and university–industry collaborations that emphasize experiential and problem-based learning can strengthen this absorptive foundation, while excessive focus on narrow doctoral specialization may yield diminishing returns for regional innovation diffusion.

Encouraging interdisciplinary career paths, through cross-domain training, internships, and collaborative projects, expands inventors' technological breadth and sustains adaptive learning across sectors. Such initiatives align with Laursen and Salter's (2006) principle that openness enhances innovative performance when managed within an optimal range.

Innovation ecosystems flourish when education, experience diversity, and mobility are cultivated together. Integrating these dimensions strengthens both the reach and depth of knowledge diffusion, creating self-reinforcing cycles of absorptive learning and technological renewal across regions and industries.

Beyond policy relevance, the findings provide several avenues for advancing theory and empirical inquiry. The results indicate that Cohen and Levinthal's (1990) construct of absorptive capacity can be effectively operationalized at the individual level through indicators such as education depth and experience diversity. This supports a multilevel perspective on absorptive capacity (Lane et al., 2006), linking micro-level learning histories to meso- and macro-level innovation outcomes. Future research should develop integrative frameworks that connect personal cognitive mechanisms with firm and regional absorptive processes, providing a more complete picture of how knowledge flows accumulate and transform across scales.

The evidence of a positive, linear relationship between knowledge breadth and spillover absorption also challenges the inverted-U paradigm embedded in the cognitive distance framework (Nooteboom, 2000). Rather than experiencing diminishing returns from diversity, individuals appear capable of continuously benefiting from varied technological exposure. Subsequent studies should examine whether the inverted-U pattern emerges only beyond a certain cognitive threshold or under conditions of excessive fragmentation of expertise.

Furthermore, the demonstrated complementarity between spatial mobility and cognitive diversity highlights the need for analytical models that integrate both dimensions as co-determinants of learning and innovation. Investigating how physical movement across regions interacts with the evolution of individuals' knowledge portfolios could reveal new insights into the micro-foundations of spillover diffusion. Employing longitudinal designs and network-based approaches would help capture these dynamic interactions and the feedback loops that sustain cumulative learning.

The results invite cross-context validation to assess the generalizability of these patterns beyond the European setting. Because institutional conditions for labor mobility vary widely, future research should examine whether similar relationships hold in contexts such as the United States or East Asia, where regulatory frameworks and cultural norms shape inventors' mobility differently. Comparative studies could explore how legal instruments, particularly non-compete clauses (Marx, Singh & Fleming, 2015), moderate the link between movement and spillover absorption. Such analyses would clarify whether the complementarity between mobility and absorptive capacity is universal or context-dependent.

6. CONCLUSION

This study provides empirical evidence that individual heterogeneity plays a decisive role in shaping the diffusion and absorption of knowledge spillovers. Using inventor-level data from the PatVal-EU survey, the findings demonstrate that inter-regional labor mobility significantly enhances the likelihood of both local and distant spillover absorption, confirming that spatial movement exposes inventors to diverse cognitive and institutional environments. These results extend the classical spatial theory of innovation by showing that the micro-level attributes of inventors are critical complements to geographical proximity.

The results underscore that innovation ecosystems thrive when spatial openness and cognitive adaptability intersect. Future research should expand on these findings through longitudinal and cross-regional comparisons to explore how institutional environments and regulatory frameworks mediate the relationship between mobility, diversity, and knowledge spillovers.

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