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# University-Industry Collaborations in European regions: the Effect of Business Cycle on diversification

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## Abstract

This paper explores the effect of the business cycle on university-industry collaborations and technological diversification within 218 European regions from 1990 to 2018. I find that university-industry collaborations increase during economic expansions, with the most pronounced effects observed in the exploitation of technologies already known to the region. In contrast, the exploration of new technologies is also positively associated with economic growth, albeit to a lesser extent. The analysis further shows that the effects of R&D investments on university-industry collaborations vary by sector over phases of the business cycle: private sector R&D expenditures are countercyclical, driving collaboration during recessions, while government R&D spending is procyclical, supporting exploratory activities during economic booms.

**Keywords:** University-Industry collaborations; business cycle, exploration

**JEL Codes:** L24; O31; O36; R11

## 1. Introduction

University-industry collaborations (UICs) are widely considered as key drivers of regional innovation systems and long-term economic growth (Liu et al., 2024; Roncancio-Marin et al., 2022). UICs serve as a critical source of external knowledge for firms by integrating universities' basic research with firms' applied research, resulting in valuable new products and processes (Fassio et al., 2018; Wirsich et al., 2016). These collaborations can also shift the balance between exploitative and exploratory innovation activities, expanding the scope of regional knowledge and fostering diversification (Rossi et al., 2022; Steijn et al., 2023). Recognizing the strategic importance of UICs, policymakers have increasingly

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implemented various schemes—such as technology transfer offices, incubators, and place-based policies—to stimulate UICs (Perkmann et al., 2013; Siegel et al., 2003).

Although the importance of UIC for the development of breakthrough inventions and the development of local ecosystems (Agrawal and Cockburn, 2003; D’Este and Patel, 2007), little is known about the effects of business cycles on university-industry knowledge co-creation and the nature of innovations within regions. Several studies have focused on the procyclicality of firms' R&D expenditures and patenting activities (Cincera et al., 2012; Fabrizio and Tzolmon, 2014; Geroski and Walters, 1995; Manso et al., 2023). Few studies have focused on the influence of period of expansion or recessions on UIC. For instance, Azagra-Caro et al., (2019) show a negative association between the great recession in 2007 and co-publications, but focusing on a single event at the country-level. At the firm-level, D’Agostino and Moreno (2018) find that during economic recessions firms tend adopt a explorative strategy through cooperations with public institutions, increasing subsequent firm innovation performance. More recently, the economic crisis triggered by the COVID-19 pandemic has underscored the pivotal role of UICs in addressing global challenges. One notable example is the collaboration between the University of Oxford and AstraZeneca, which successfully developed and distributed a vaccine candidate initiated by academic research (Druehdahl et al., 2021). The pandemic has increased public awareness of UICs’ potential to address societal needs. This increased visibility provides an opportunity to expand such collaborations beyond this crisis, fostering long-term partnerships that contribute to broader societal and economic resilience.

This paper seeks to address this gap by examining the pro- or countercyclical response of UIC to the business cycles of European regions. More specifically, the paper aims to understand whether UIC in periods of expansions and recessions correlated to an exploration strategy, leading to the introduction of previously unexplored inventions (D’Agostino and Moreno, 2018; March, 1991). To this end, I take advantage of the RegPat and the OECD's Harmonised Applicant Names (HAN) databases, which include patent applications and georeferenced inventors at the European Patent Office (EPO) to measure collaborations for all organizations located in 218 European NUTS-2 regions from 1990 to 2018. This dataset allows for the identification of patents co-assigned between universities, public research institutes, and firms, providing a measure of UIC activity. Following recent innovation literature (Manso et al., 2023; Silvestri et al., 2018), I also introduce two patent-based measures that differentiate between patents filed in new and old technology classes, capturing the introduction of breakthrough and known technologies from UIC across time within each region. Supplemented

with regional economic characteristics, this dataset facilitates a long-term analysis of regional UIC activity. Using a panel regression specification, I explore how economic fluctuations influence the inventions generated by universities and co-located firms, with a particular focus on their impact on the entry of novel technological domains.

The findings indicate a positive association between patenting from UICs and GDP growth in regions. Over the business cycle, UICs are primarily driven by the introduction of technologies already known within the region, while the introduction of new technologies also increases but to a lesser extent. These results suggest that both known and new technology entries through UICs exhibit procyclical behavior, rising during periods of economic expansion. In terms of magnitude, a one-percentage-point increase in GDP growth is associated with a 1.02 percent increase in the number of UICs. This effect is primarily driven by the development of known technologies, which rise by 0.99%, whereas new technologies show a more modest increase of 0.23%. However, additional analysis shows that this increased over the business cycle does not translate into higher patent quality, as measured by forward citations. These findings are robust across a variety of alternative measures, transformations of the dependent variables, estimation methods, and subsamples.

Finally, I explore the heterogeneity of UIC over the business cycle according to the source of R&D. Specifically, I investigate whether the R&D performed by firms, government, and higher education moderate the procyclicality of UIC. I find that the number of UICs and the introduction of technologies known to the regions decrease over the business cycle with R&D performed by the private sector. In contrast, the emergence of new technologies is procyclical with R&D performed by the public sector. This heterogeneity according to the R&D sectors highlights the strategic asymmetries across the private and public sectors for promoting UICs.

The remainder of the paper is organized as follows. Section 2 discusses the theoretical background on how UIC varies over the business cycles, with an emphasis on the resulting entry of novel or old technologies within regions. Section 3 presents that data, while Section 4 describes the empirical approach. Finally, Sections 5 and 6 present the empirical findings and discusses the conclusions with policy implications.

## 2. Literature review

Beyond teaching and scientific research roles of universities, the triple helix model (Etzkowitz and Leydesdorff, 2000) states that universities also play an essential role in strengthening knowledge societies through collaborations with firms and government entities. As a result,

universities are recognized as key drivers of innovation, producing new basic research that fosters regional economic growth through knowledge spillovers (Hausman, 2022; Jaffe, 1989). Firms can rely on basic research through collaborations with universities and public research organizations, creating new technological opportunities and converting ideas into commercialized innovations (Cohen et al., 2002).<sup>2</sup> Furthermore, recent evidence suggests that UICs can mitigate the negative effects of economic recessions on firms' R&D investments and patents, as a strategy in response to macroeconomic fluctuations (Añón Higón and Vicente-Chirivella, 2024; D'Agostino and Moreno, 2018; Trantopoulos et al., 2024). This paper contributes to the literature on the cyclical nature of innovation. While much of the evidence focuses on the impact of the business cycle on firms' R&D expenditures and patenting, less is known about its impact on collaborations between universities and firms.

A large body of theoretical works supports the countercyclical nature of innovation, suggesting that periods of recessions are the engine of the introduction of new technologies from firms (Schumpeter, 1939). During downturns, firms tend to prioritize productivity-enhancing activities over production due to reduced demand. This reallocation occurs because the opportunity cost of innovating is lower during recessions (Aghion and Saint-Paul, 1998; Saint-Paul, 1997). Consequently, firms allocate more resources to developing new products, as the expected returns from existing products are diminished. While internal R&D remains a significant source of innovation, external collaborations with universities and public research organizations also play a crucial role in generating new knowledge. UICs, in particular, serve as effective channels for accessing basic research, which has been shown to contribute more significantly to firm productivity than other R&D sources (Czarnitzki and Thorwarth, 2012; Miotti and Sachwald, 2003). Relying on public partnerships involves a lower risk of leakage that could be cost-effective by mitigating financial constraints, especially when internal R&D investments are scaled back due to budget constraints (Bercovitz and Feldman, 2007; Cincera et al., 2012). Thus, collaborations with universities during downturns can allow firms to maintain a pipeline of innovation while mitigating financial risk (Audretsch and Feldman, 2004; Caloghirou et al., 2021). Moreover, relying on large networks that include universities could be beneficial during periods of recession by increasing the sources of diverse knowledge and hence increasing patenting activities (D'Agostino and Moreno, 2018). This implies a negative relationship between the business cycle and firms' scientific collaborations with universities.

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<sup>2</sup> Collaboration through patenting is one realization of academic engagement with the industry. Beyond co-patenting, interactions across universities and firms include research contracts, licensing, sharing specialized equipment, and informal activities such as advice (D'Este and Patel, 2007; Perkmann et al., 2013).

In contrast, another strand of works suggests that innovation is procyclical, intensifying during periods of economic expansion. Firms face higher demand for goods and services that positively affect R&D investments (Shleifer, 1986). Thus, firms face lower financial constraints and can better allocate resources toward innovation activities (Barlevy, 2007; Hall, 2002). Moreover, access to external finance from banks increases during periods of expansion (Aghion et al., 2012). As a result, UICs could increase with the business cycle. Despite the benefits of acquiring external basic knowledge from universities, coordination, and transaction costs with universities' divergent objectives could hinder firms' incentive to collaborate (He et al., 2021; Laursen and Salter, 2006), especially when the availability of internal liquidity is high (Hall, 2002).

Empirical evidence on the evolution of inventions patented by UICs is still limited. Most of the literature has focused on firm responses to the business cycle, documenting the cyclicity of R&D and patents (e.g., (Barlevy, 2007; Cincera et al., 2012; Fabrizio and Tzolmon, 2014; Manso et al., 2023; Silvestri et al., 2018). Few exceptions explore the UICs over the business cycle. For instance, Azagra-Caro et al. (2019) examine the impact of the Great Recession (2007-2008) on the scientific co-productions between universities and the private sector using a sample of OECD countries. They found a negative relationship between the macroeconomic cycle and the university-industry publications. This relationship is more pronounced for collaborations between innovative actors located within the same country. In contrast, Gómez-Aguayo et al. (2024) show, for a sample of Spanish firms, that the probability of co-publications decreases in periods of expansions, therefore supporting the countercyclical arguments. Moreover, the authors find an inverted U-shaped relationship between GDP growth and the likelihood of co-publications. As a result, the procyclical relationship between firms' patented discoveries and the economic cycle is likely to impact UICs.

Beyond the raw number of patents, the nature of inventions arising from UICs may vary with the business cycle. Universities have a role in promoting innovation dynamics and establishing technical trajectories at the regional level. Interactions with the industrial sector influence knowledge recombination and the adoption of new technologies (Caviggioli et al., 2020; D'Este and Patel, 2007). Thus, open innovation strategies that integrate basic knowledge through collaborations with universities can shift toward exploring new technologies during recessions (Añón Higón and Vicente-Chirivella, 2024; D'Agostino and Moreno, 2018). According to March (1991), exploration involves search, experimentation, and the development of novel products, while exploitation focuses on refining existing ideas. Economic recessions may encourage firms to reallocate R&D activities toward an exploration strategy. The

underlying argument is that recessions lower the opportunity costs faced by firms, offering incentives to allocate resources for conducting new searches (Manso et al., 2023; Silvestri et al., 2018). For instance, Manso et al. (2023) find that while R&D expenditures and patent counts remain procyclical, firms tend to adopt exploration approaches to innovation during downturns, indicating a countercyclical shift in strategy. Silvestri et al. (2018) investigate the relationship between the industry cycle and the recombination of knowledge into new technologies. The authors find that during recessions, firms reduce innovative search. However, the technological impact and market value of these inventions tend to be higher during periods of recession. Thus, UICs are particularly well-suited for supporting exploration during recessions, as they provide access to external knowledge and research infrastructure (Bercovitz and Feldman, 2007; Rosenkopf and Nerkar, 2001). This suggests that the relationship between UICs and exploration may strengthen during recessions compared to expansions, facilitating the emergence of new technologies.

### 3. Data and summary statistics

This paper examines the cyclicity of university-industry collaborations (UIC) and investigates whether such collaborations lead to the development of technologies that are new to the region or reinforce existing regional technologies. The analysis covers 218 European NUTS-2 regions (EU28, plus Island, Montenegro, Macedonia, and Norway)<sup>3</sup>, over the period 1990 to 2018. I use the delimitations of 2021 as the definition of NUTS-2 regions. I gather data from several sources. The first source is the OECD's RegPat database, which contains information on patent-inventor applications and the associated list of Cooperative Patent Classification (CPC) for all patents in the dataset. The other sources are the Cambridge Econometrics European Regional Database (ARDECO) and the Quality of Government EU Regional dataset, which provide regional administrative data.

#### 3.1. Measuring UIC, known and new technologies

I use patent application data from the European Patent Office (EPO) to measure university-industry collaborations at the regional level. Following the literature on UICs (Caviggioli et al., 2023; Quignon, 2023), the first dependent variable is the number of patents co-assigned between public institutions (including universities) and firms. To identify these patents, I use standardized applicant names from the OECD's Harmonised Applicant Names (HAN) database,

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<sup>3</sup> Appendix Table A.1 reports the list of NUTS-2 included in the main analysis with corresponding codes.

and I manually check the names to avoid false positives. UIC patents are assigned to regions based on the registered addresses of inventors listed in patent documents. For patents with multiple inventors in different regions, I proportionately distribute patents to regions by allocating a share to each region equal to the inverse of the number of inventors to avoid multiple counting. Over the sample period, 14,240 UIC patents were filed by 44,411 inventors.

The second dependent variable, following the literature on regional innovation specialization (Boschma et al., 2013; Caviggioli et al., 2023), captures the number of technologies from UIC that are known to a region (**Known Tech.**). UIC patents are classified as known if, within the same technology class (based on the n=672 CPC at the four-digit level), at least one other patent was filed in the region in the previous 1 to 5 years. In contrast, UIC patents in technology classes with no prior filings within this timeframe are classified as new to the region, which corresponds the third dependent variable. This variable aims to capture whether the business cycles lead to the entry of new technologies from UIC. These variables are constructed as follows:

$$New\ Tech_{it} = \sum_{c=1}^c UIC_{ict} p_{ict-1;\dots;t-5} \quad (1)$$

$$Known\ Tech_{it} = UIC_{it} - New\ Tech_{it} \quad (2)$$

where  $U_{ict}$  represent the number of patents in technology class  $c$  filed at time  $t$  by inventors residing in region  $i$ , and  $p_{i,c,t-1\dots t-5}$  represent the fraction of all patents filed in region  $i$  between years  $t-5$  and  $t-1$  that belong to technology class  $c$ . The variable **Known Tech.** equals the count of UIC patents if the distribution of UIC patents across technology classes in year  $t$  matches the distribution of all patents filed in the previous five years within region  $i$ , and zero otherwise. In contrast, **New Tech.** captures the count of UIC patents if the distribution of UIC patents across technology classes in year  $t$  represents a new entry in a given class within the prior five years.<sup>4</sup> I use the logarithm transformation plus one ( $\log +1$ ) the number of one of the three dependent variables.

Finally, to address concerns that UIC patents may not fully reflect the quality of joint innovation, I use the log of the average number of forward citations received by UIC patents within five and seven years as the dependent variable. The number of forward citations is divided by the total number of UIC patents filed in a given region-year. Forward citations serve

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<sup>4</sup> As a robustness check, I use a three-year timeframe to measure these dependent variables.

as a proxy for patent quality, with higher citation counts indicating greater market value (Hall et al., 2005; Kline et al., 2019).

### 3.2. Measuring business cycles

To examine the cyclicity of university-industry collaborations (UIC), I focus on the growth rate of GDP at the NUTS-2 level (**GDP growth**), measured annually (Bloom et al., 2018). GDP is expressed in millions of euros at constant 2015 prices. To further explore whether UIC responds asymmetrically to economic expansions and recessions, I also use a recession indicator variable (**Recession**), which equals one if the GDP growth rate is negative, and zero otherwise. This recession indicator is region- and year-specific.

### 3.3. Moderating roles of R&D spending

To examine whether UIC varies over economic cycles based on the sectors conducting R&D activities, I extend the baseline specification by incorporating interaction terms. Specifically, I interact GDP growth with R&D spending by the private, public, and higher education sectors. R&D spending is measured as intramural expenditure per inhabitant in euros, encompassing both current expenditures and gross fixed capital formation in R&D. To account for the time lag between research activities and patent applications, these variables are lagged by one year. Recent evidence highlights an average two-year lag between a negative federal funding shock and patenting (Babina et al., 2023). However, Griliches (1990) finds that the lag between initial research and patent application is low.

### 3.4. Control variables

Several variables are included at the region levels to control for other characteristics are correlated with the number of UIC. Previous studies argue that the structure of interactions within region can foster the emergence of new technologies through collaborations. The geographical proximity among actors (i.e., firms and public organizations) increase the number of potential interactions and the formation of new relationships (e.g., Quignon, 2023; Wanzenböck et al., 2024). Furthermore, the spatial agglomeration of economic activity enhances local knowledge spillovers, further supporting innovation. To control for the structure of internal interactions, I follow Wanzenböck et al. (2024) who introduce the ratio of the number intra-regional collaborations (i.e., organizations) to the number of inter-regional collaborations in region  $i$  and time  $t$ . This variable is defined as follows:

$$RIC_{it} = \frac{Intra - Collab_{it}}{Inter - Collab_{it}} \quad (3)$$

A high value of region-internal orientation implies a greater proportion of partnerships with intra-regional partners, while a comparatively low value shows a preference for collaborations with foreign partners.

Drawing on the technological relatedness (Boschma, 2015; Steijn et al., 2023), the emergence of new technologies is influenced by the proximity to technologies previously developed within a region. Following Hidalgo et al. (2007), I control for the technological relatedness between the set of new and existing technologies of the region using the relatedness density measure. Specifically, relatedness density is defined as follows:

$$RDens_{it} = \frac{\sum_{j \in c, j \neq i} TR_{ijt}}{\sum_{j \neq i} TR_{ijt}} \times 100 \quad (4)$$

where  $\sum_{j \in c, j \neq i} TR_{ijt}$  is the sum of technological relatedness values of the technologies in the region to the potential entering technology and  $\sum_{j \neq i} TR_{ijt}$  is the sum of relatedness values of all technologies to this potential new technology class. Both values used the relatedness measure proposed by Steijn et al. (2023) that measures the frequency that two technologies ( $i$  and  $j$ ) co-occur in patent applications in time  $t$  compared to a random distribution (Steijn et al., 2023).

I also control for regional size using the log of total population at the NUTS-2 level<sup>5</sup>, the log of stock of capital at constant prices which is related to the production technology (Liu et al., 2024), and the log of stock of patent (excluding UIC patents) following Miguelez and Morrison (2023). Finally, I control for the log of intramural R&D expenditure per inhabitant to estimate the relationship between research in the previous period and patent applications consistent with the previous literature (Manso et al., 2023; Montresor and Quatraro, 2017).

Appendix Table 2 provides the definition of the variables used in the study and their corresponding data sources. Table 2 reports the summary statistics. On average, the number of UICs per year is 1.83, including 1.77 of known and 1.03 of new technologies. The regional GDP has grown at the rate of 0.018 between 1990 and 2018. In addition, Table 3 shows the pairwise correlations among the main variables of interest and control characteristics.  $\log(\text{UIC})$  and  $\log(\text{Known Tech.})$  exhibit a strong correlation with each other (0.995,  $p < 0.000$ ), while

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<sup>5</sup> I also control for region size using the lagged level of GDP or GDP per capita. The results are similar than in the baseline specification.

their correlation with  $\log(\text{New Tech.})$  is more modest (0.443,  $p < 0.000$ ). As expected, both variables are correlated with  $\log(\text{R\&D})$ , but to a lesser extent for  $\log(\text{New Tech.})$ . Lastly, the business cycle (GDP growth) shows a negative correlation with all three dependent variables.

Table 1. Summary Statistics

Variable	N	Mean	SD	Min	Max
$\log(\text{UIC})_t$	4,112	0.605	0.863	0	5.216
$\log(\text{New Tech.})_t$	4,112	0.071	0.179	0	1.609
$\log(\text{Known Tech.})_t$	4,112	0.574	0.855	0	5.210
$\log(\text{Avg fwd5})_t$	4,112	0.345	0.618	0	4.888
$\log(\text{Avg fwd7})_t$	4,112	0.419	0.695	0	5.071
GDP Growth $_t$	4,112	0.018	0.031	-0.177	0.281
Recession $_t$	4,112	0.204	0.403	0	1
$\log(\text{R\&D Firm per inhabitant})_{t-1}$	2,838	4.181	1.588	0	7.689
$\log(\text{R\&D Government per inhabitant})_{t-1}$	3,023	2.926	1.401	0	6.210
$\log(\text{R\&D Higher Educ. per inhabitant})_{t-1}$	3,008	3.765	1.318	0	7.690
$\log(\text{Population})_{t-1}$	4,112	14.13	0.881	10.13	16.30
$\log(\text{R\&D})_{t-1}$	4,112	5.110	1.411	0	8.265
$\log(\text{Patent})_{t-1}$	4,112	3.662	1.973	0	8.103
$\log(\text{Stock Capital})_{t-1}$	3,632	11.24	1.202	6.997	14.42
RIC $_{t-1}$	3,661	0.009	0.021	0	0.392
RDens $_{t-1}$	3,864	28.83	31.20	0	100

#### 4. Empirical framework

To estimate the effect of changes in business cycles in UICs, known and new technologies, I estimate the following equation via OLS:

$$y_{it} = \beta_1 \text{GDP Growth}_{it} + \beta_2 X_{it-1} + \delta_i + \delta_t + \varepsilon_{it} \quad (5)$$

where  $y_{it}$  is either the log plus one of UICs, known, and new technologies resulting from UIC in region  $i$  during year  $t$ . The main variable of interest is the GDP Growth in region  $i$  during year  $t$ , which captures the business cycles. A positive estimated coefficient suggests that UICs are procyclical, while a negative estimated coefficient indicates that UIC are countercyclical.  $X_{it-1}$  is a set of one-year lagged time-varying region-specific variables as defined in Section 3.4.  $\delta_i$  are region fixed effects that control for time-invariant unobservable region-specific characteristics.  $\delta_t$  are year fixed effects that purge the estimates from unobservable common trends to regions, and  $\varepsilon_{it}$  denotes the error term. Standard errors are clustered at the region level to account for heteroskedasticity and serial correlation within European regions.

Controlling for lagged region-specific characteristics and the full set of fixed effects should reduce concerns about reverse causality or the impact of unobservable factors that could simultaneously affect UICs and the business cycles. For instance, booms result in greater resources available to conduct innovation activities (e.g., R&D investments and patents) and induce additional financial resources for universities and firms, stimulating economic growth (Tseng et al., 2020). As a result, that could lead to an upward bias and fail to find countercyclicality. To address these concerns, I use a Generalized Method of Moments (GMM) estimator with a lagged dependent variable (Arellano and Bond, 1991). This GMM approach enables to correct for bias due to lagged endogenous variables in dynamic panel data. Specifically, I estimate the following specification:

$$y_{it} = \beta_1 y_{t-1} + \beta_2 GDP\ Growth_{it} + \beta_3 X_{it-1} + \delta_i + \delta_t + \varepsilon_{it} \quad (6)$$

The baseline specification is extended in several fashions to explore further the role of economic downturns, the persistence of negative shock on the introduction of patent inventions from UICs, and the heterogeneous effects according to the sector conducting R&D spending. First, I replace GDP growth with a dummy variable equal to one for a period of negative growth to determine whether the entry of new or existing technologies decreases significantly after a period of recession. Then, I explore the persistence of a business cycle shock on either UICs or known and new technologies. For that purpose, I use an alternative specification based on the local projection (LP) method proposed by (Jordà, 2005). This specification allows us to estimate impulse response functions to each economic shock in a flexible way through OLS. The LP approach implies running a set of linear regressions of future realizations of the dependent variable on the current values of a set of control variables, which include the unitary shock. Following Jordà and Taylor (2024), the specification used is lagged augmented with a one-period lag for the shock and the control variables as in equation (1). Specifically, the local projection specification is as follows:

$$y_{it+h} = \beta_1 y_{it-1} + \beta_h GDP\ Growth_{it-h} + \sum_{j=1}^k \beta_j X_{it-j} + \delta_i + \delta_t + \varepsilon_{it+h} \quad (7)$$

where  $y_{it+h}$  is one of the dependent variables used previously in region  $i$  in year  $t+h$ . The coefficient of interest is  $\beta_h$ , which estimates the effect of a business cycle shock at time  $t$  on the

UIC, known, and new technologies' reaction at time  $t + h$ .  $\varepsilon_{it+h}$  denotes the error term at each horizon. I estimate local projections for 6 periods after the occurrence of each event ( $h = 1, \dots, 6$ ) that allows to observe the evolution of the impact over a longer period.<sup>6</sup> Finally, I introduce an interaction term between GDP growth and R&D spending by sectors to explore the heterogeneous effects as discussed in Section 3.3.

## 5. Results

Table 2. Baseline Effects

Dep. Var.	log(UIC)		log(Known Tech.)		log(New Tech.)	
	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth $_t$	1.419** (0.591)	1.022*** (0.292)	1.384** (0.599)	0.987*** (0.275)	0.157 (0.116)	0.230* (0.123)
log(Population) $_{t-1}$	0.255*** (0.064)	1.388** (0.559)	0.248*** (0.063)	1.400** (0.562)	0.028** (0.011)	0.228* (0.123)
log(Stock Capital) $_{t-1}$	0.086 (0.057)	-0.660*** (0.176)	0.083 (0.057)	-0.659*** (0.178)	0.014 (0.010)	-0.076** (0.036)
log(Total R&D) $_{t-1}$	0.169*** (0.053)	-0.124** (0.054)	0.167*** (0.053)	-0.131** (0.053)	0.015 (0.010)	-0.000 (0.012)
log(Patent) $_{t-1}$	0.126*** (0.033)	0.090*** (0.031)	0.132*** (0.033)	0.082*** (0.030)	-0.007 (0.006)	0.021** (0.008)
RIC $_{t-1}$	0.299 (0.958)	-0.839 (0.607)	0.207 (0.926)	-0.792 (0.585)	0.323 (0.225)	-0.133 (0.167)
RDens $_{t-1}$	0.004*** (0.001)	0.010 (0.007)	0.005*** (0.001)	0.011 (0.007)	-0.000** (0.000)	-0.000 (0.001)
N	3232	3231	3232	3231	3232	3231
R <sup>2</sup>	0.516	0.799	0.521	0.805	0.071	0.246
Region FEs	No	Yes	No	Yes	No	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

### 5.1. Baseline results

Table 3 reports the results of the baseline specification using the log of UIC, known and new technologies as dependent variables to investigate the response to the cyclicity, without and with region fixed effects. In columns (1) and (2), the estimated coefficients of GDP growth are positive and statistically significant, suggesting that UIC increase with the growth of the

<sup>6</sup> The sample period prevents me from estimating the persistence of business cycle shock over a longer period  $h$ .

Table 3. UICs during crises

Dep. Var.	log(UIC)	log(Known Tech.)	log(New Tech.)
	(1)	(2)	(3)
Recession <sub>t</sub>	-0.038 (0.024)	-0.046* (0.024)	0.005 (0.010)
log(Population) <sub>t-1</sub>	1.371** (0.557)	1.387** (0.559)	0.220* (0.123)
log(Stock Capital) <sub>t-1</sub>	-0.686*** (0.176)	-0.683*** (0.177)	-0.084** (0.036)
log(R&D) <sub>t-1</sub>	-0.130** (0.054)	-0.137** (0.053)	-0.001 (0.013)
log(Patent) <sub>t-1</sub>	0.093*** (0.031)	0.085*** (0.030)	0.022** (0.009)
RIC <sub>t-1</sub>	-0.856 (0.610)	-0.811 (0.587)	-0.135 (0.169)
RDens <sub>t-1</sub>	0.010 (0.007)	0.011 (0.007)	-0.000 (0.001)
N	3231	3231	3231
R <sup>2</sup>	0.798	0.804	0.245
Region FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

regional economy. This estimate indicates that a one percentage point increase in GDP growth increases the number of UICs by 1.02 percent. As expected with the correlation coefficient reported in Table 3, the relationship between log(Known Tech.) and the GDP growth is positive and statistically significant (columns 3 and 4). A one percentage point increase in GDP growth increases the number of UICs' patents in the existing technological domains by 0.99 percent. In column 5 for the entry of new technologies, the estimated coefficient of GDP growth is positive but statistically insignificant when regional fixed effects are excluded. Controlling for region fixed effects in column 6, the estimated coefficient is still positive, but statistically significant. This estimate indicates that a one percentage point increase in GDP growth is associated with a 0.23 percent increase in UIC patents in new technology domains. These results suggest that

the entry of new technologies from UIC is procyclical as the number of UIC and known technologies, but slightly smaller in magnitudes.<sup>7</sup>

To further test the cyclicity of UIC, I extend the baseline specification by replacing the GDP growth with a dummy variable which indicates if a region is experiencing a recession (Recession) or not in time  $t$ . Recession is equal to one if the GDP growth is negative. In column (1) for UIC, the estimated coefficient of Recession is negative, but statistically insignificant at conventional levels. In contrast, the coefficient is still negative but statistically significant for known technologies (column 2). A recession is associated with a decrease of 4.6 percent in UICs in existing technologies. Whereas it is positive and statistically insignificant for the entry of new technologies in column 3. These results are, to some extent, consistent with the procyclicality of patenting from UICs, which rests on known technologies. While new technologies are not sensitive (i.e., acyclical) to periods of downturns but increased slightly with the business cycles.

## 5.2. Robustness checks

In this section, I conduct several robustness checks on the baseline results using alternative estimators, transformations of the dependent variables, and various samples.

The dynamics of UIC and the corresponding introduction of technologies can influence current outcomes, potentially biasing estimates of the effect of GDP growth on UIC patenting. To address this, I estimate a full linear dynamic panel model for UIC, including a one-year lag of the dependent variables. Results are presented in Table 4 and indicate that the conclusions remain robust under these dynamic specifications. Furthermore, the estimated coefficients for the lagged dependent variables are positive and statistically significant, suggesting that UIC and the introduction of known technologies are persistent over the short term.<sup>8</sup>

As discussed in Section 4, the baseline specification may still be affected by reverse causality between the dependent variables and business cycles, as well as by omitted variable bias. To address these endogeneity concerns, I employ a GMM estimator, which provides consistent estimates for dynamic panel models (Arellano and Bond, 1991). The GMM approach uses lagged values of the dependent variable as instruments to control for reverse causality.

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<sup>7</sup> These results are robust to excluding Finland, Norway, and Sweden where the “professor privilege” was in force until 2007, 2002, and 2003, respectively. This policy held full rights to university researchers for intellectual property created, which can bias the measure of UICs.

<sup>8</sup> However, the estimated coefficient of the lagged of new technologies is positive but insignificant, which suggests more occasional development of novel inventions by UIC.

Table 4. Dynamic Specifications

Dep. Var.	log(UIC) (1)	log(Know Tech.) (2)	log(New Tech.) (3)	log(UIC) (4)	log(Know Tech.) (5)	log(New Tech.) (6)
log(Population) <sub>t-1</sub>	0.667* (0.351)	0.658* (0.336)	0.086 (0.113)	0.218*** (0.044)	0.198*** (0.042)	0.037*** (0.012)
log(Stock Capital) <sub>t-1</sub>	-0.401*** (0.133)	-0.366*** (0.127)	-0.135*** (0.041)	0.044 (0.050)	0.041 (0.048)	0.006 (0.013)
log(R&D) <sub>t-1</sub>	-0.035 (0.041)	-0.043 (0.040)	0.003 (0.014)	0.184*** (0.042)	0.168*** (0.040)	0.028** (0.012)
log(Patent) <sub>t-1</sub>	0.009 (0.023)	0.009 (0.021)	0.011 (0.009)	0.137*** (0.028)	0.137*** (0.026)	-0.001 (0.008)
RIC <sub>t-1</sub>	-0.653 (0.503)	-0.400 (0.444)	-0.229 (0.213)	-0.629 (0.637)	-0.420 (0.578)	-0.102 (0.310)
RDens <sub>t-1</sub>	0.010 (0.007)	0.010 (0.007)	0.001 (0.001)	0.004*** (0.001)	0.004*** (0.001)	-0.000 (0.000)
log(UIC) <sub>t-1</sub>	0.418*** (0.047)			0.221*** (0.040)		
log(Known Tech) <sub>t-1</sub>		0.451*** (0.047)				
log(New Tech.) <sub>t-1</sub>			0.054 (0.033)			
GDP Growth <sub>t</sub>	0.711** (0.294)	0.616** (0.282)	0.300** (0.143)	1.021** (0.433)	0.880** (0.396)	0.362* (0.190)
N	2331	2331	2331	2283	2283	2283
R <sup>2</sup>	0.848	0.857	0.279			
N. Instruments				87	87	87
AR(1) p-value				0.000	0.000	0.000
AR(2) p-value				0.072	0.127	0.471

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Consistent with the dynamic panel estimates, the GMM results in columns 4 to 6 align with the preferred specification in Table 3.

As a second set of robustness, I estimate the baseline specification with alternative transformations of the dependent variables. Specifically, I use a three-year window instead of a five-year window to measure known and new technologies and the inverse hyperbolic sine

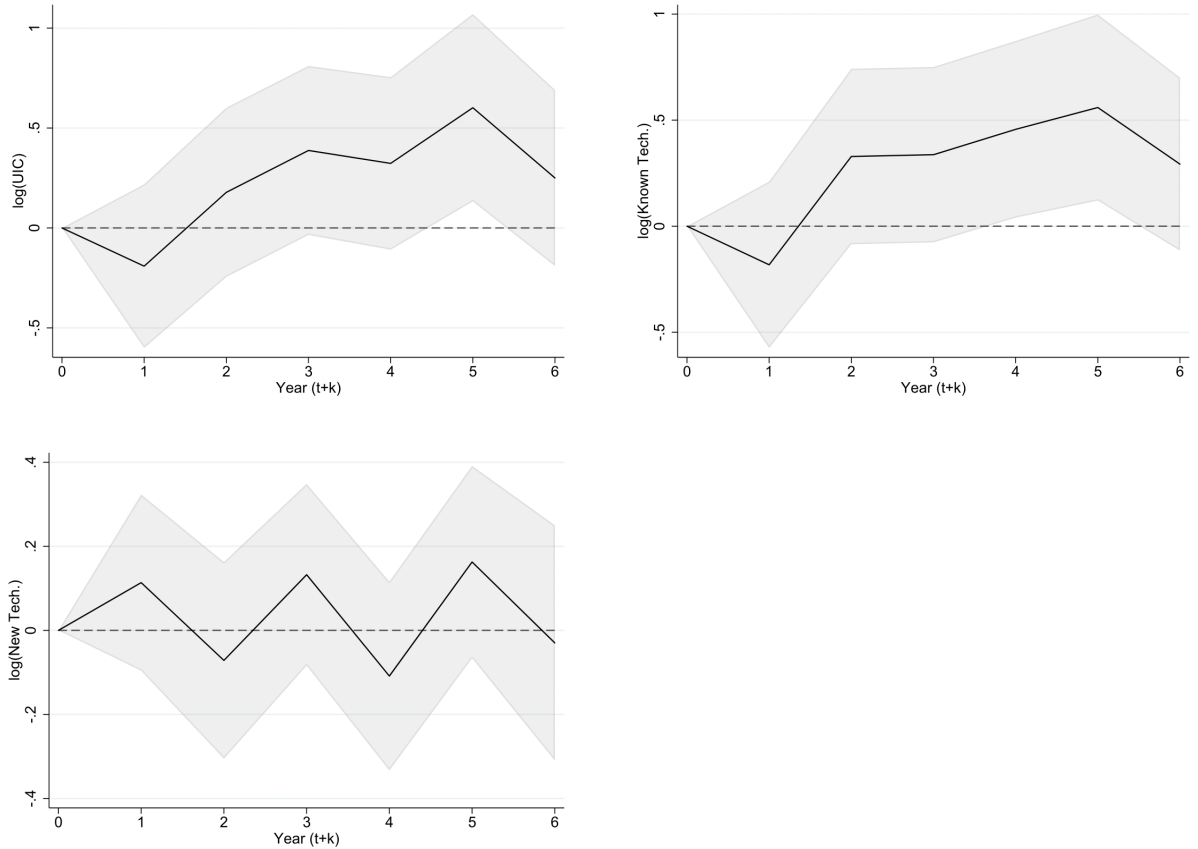


Figure 1: Response of UICs to shocks to GDP growth

transformation instead of the logarithmic transformation.<sup>9</sup> In Appendix Table A. 4, I show that the results are robust to these alternative transformations.

Finally, I perform additional robustness checks, which control for the influence of the set of control variables used, by introducing sequentially the control variables, using different lags (i.e., two- and three-year lags), checking for outlier regions by excluding region-year without UIC, and region-year at the 95<sup>th</sup> percentile of UIC distribution. Results remain robust to these additional robustness checks (see Appendix Tables A. 5 to A. 11).

### 5.3. Further explorations

After highlighting that patenting from UIC is increasing with the business cycle, I next examine the long-lasting effects of an economic shock using the LP approach described in Section 4. Figure 1 shows the impulse response functions with 90% confidence intervals for the effects of a unit shock in GDP growth (i.e., recession) on patenting from UIC. Consistent with the regression results in Table 4, I observe a negative effect on log(UIC) in the year following the

<sup>9</sup> All regressions are also robust to estimate the baseline specification through OLS in levels.

negative shock (Panel A). Then, the effect reverses over the next year, with a positive effect on  $\log(\text{UIC})$  lasting 4 years, albeit not statistically significant at conventional levels. A similar pattern emerges for the entry of technologies known, with an increase persistent from the second year after the negative shock. There appears to be a delayed recovery following a period of recession that allows UICs to catch up on the delay incurred due to a negative shock. Collaborative projects resume during a period of expansion, preventing a lasting loss of innovation at the regional level. These results are consistent with Manso et al. (2023), which suggest that firm patenting, especially exploitation of known technologies concentrates during periods of expansions. In contrast, a unit shock in GDP Growth does not have any significant effect on  $\log(\text{New Tech.})$  over the next 6 years, suggesting no reactions of UICs to recessions for introducing explorative patents. This result contrasts with previous evidence that U.S. cities are negatively impacted by recessions with reduced diversification (Steijn et al., 2023).

Table 5. Average Patent Value

Dep. Var.	$\log(\text{Avg fwd5})$	$\log(\text{Avg fwd7})$
	(1)	(2)
GDP Growth <sub>t</sub>	0.437 (0.518)	0.052 (0.565)
$\log(\text{Population})_{t-1}$	-0.427* (0.224)	-0.728*** (0.239)
$\log(\text{Stock Capital})_{t-1}$	-0.042 (0.152)	0.112 (0.158)
$\log(\text{Total R\&D})_{t-1}$	0.026 (0.038)	0.010 (0.044)
$\log(\text{Patent})_{t-1}$	0.080*** (0.026)	0.084*** (0.032)
RIC <sub>t-1</sub>	-0.546 (0.410)	-0.990** (0.441)
RDens <sub>t-1</sub>	0.001 (0.001)	-0.000 (0.002)
N	3231	3231
R <sup>2</sup>	0.274	0.299
Region FEs	Yes	Yes
Year FEs	Yes	Yes

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Patents, from UICs, firms, or public organizations vary widely in quality and value. Do patents by UIC have a higher value? Schumpeter (1939) argues that high-quality inventions should be countercyclical, increasing during downturns. Recessions are periods of creative destruction that foster exploration and breakthrough inventions. Downturns that induce higher financial constraints in the corporate sector shift the focus to novel ideas and enhance the productivity of firms (Makridis and McGuire, 2023; Manso et al., 2023). However, negative shocks affecting the funding of researchers can lead to an increase in lower quality patented innovations (Babina et al., 2023). Because UIC increased during expansions, concentrated in technologies already patented in the previous year, I could expect the average value of patents to decrease. To examine whether innovation quality responds to the business cycles, I consider the average number of citations received by UIC patents over the subsequent five and seven years. In columns 1 and 2 of Table 6, estimated coefficients are positive but statistically insignificant, suggesting that the future citations to UIC patents are insensitive to the business cycles. Combined with the increase in the number of patents filed by UIC, this result suggests that the increase might be driven by lower-quality ideas rather than an increase in patents receiving more forward citations.

So far, the baseline results show that patenting by UIC, in technologies known, and new to the region is procyclical, decreasing during downturns. However, variations in R&D funding sources over the business cycle may lead to different UIC responses. Several studies have documented a positive relationship between the number of UICs and R&D expenditures by both businesses and higher education institutions (Azagra-Caro et al., 2019; Giunta et al., 2016). However, the influence of the business cycle on UICs may differ depending on whether the R&D spending originates from private or public sources. For instance, economic downturns often impose financial constraints that reduce private sector R&D investments, whereas governments may adopt countercyclical policies aimed at sustaining or increasing UIC during such periods. Motivated by these considerations, I explore these heterogeneities by introducing an interaction term between GDP growth and R&D spending by firms, government, and higher education sectors. The results are presented in Table 7.<sup>10</sup> Columns 1 and 4 show a positive that the number of UICs and the introduction of known technologies increase when economy expands, confirming the procyclicality relationship previously highlighted. Business R&D expenditures are associated with a decrease in the number of UICs and known technologies. Interestingly, the interaction term between GDP growth and business R&D expenditures shows

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<sup>10</sup> For conciseness, the control variables are not reported in Table 7 but include the same set than in the baseline specification, with the exception of  $\log(\text{R\&D})$  t-1.

that the negative R&D expenditures by the private sector on the number of UICs generated and UICs in existing technological domains according to the phase of the business cycle.<sup>11</sup> In other words, business R&D expenditures in periods of expansion are associated with a decrease both in UICs and known technologies, suggesting a countercyclical response of the private sector in engaging in collaborations with public organizations and resulting in introducing existing technologies into regions. Whereas the interaction term is positive but statistically insignificant for the emergence of new technologies, suggesting that private sector R&D is acyclical with the business cycle. Concerning the effect of government and higher education R&D spendings, the estimated effects statistically insignificant on UICs, exploitative, and exploratory inventions. However, column 8 shows a positive and significant interaction between GDP growth and government R&D spending, specifically for the introduction of new technologies. This result suggests that government R&D expenditures in periods of expansion are associated with an increase in exploratory inventions within a region. Consistent with Azagra-Caro et al. (2019), firms' R&D activities are countercyclical while engaging in UIC, however novel discoveries resulting from UIC are predominantly driven by public sector R&D during economic booms.

Taken together, these results provide novel insights on the cyclicity of patenting from UICs. In particular, I find that collaborations between public organizations and firms resume rapidly following recessions, confirming their procyclicality; however, these collaborations do not lead to more breakthrough inventions. In addition, firms adopt countercyclical strategies, increasing R&D spending during recessions, which supports higher patenting activity in subsequent periods (i.e., expansions). In contrast, government sector R&D spending remains procyclical and contributes to a greater number of novel inventions emerging from UIC.

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<sup>11</sup> The results are robust and similar in magnitude when using R&D spending by firms without one-year lag.

Table 6. Heterogeneous Effects by R&amp;D Sources

Dep. Var.	log(UIC)			log(Know Tech.)			log(New Tech.)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP Growth <sub>t</sub>	2.512*** (0.863)	0.376 (0.575)	1.121** (0.555)	2.678*** (0.790)	0.634 (0.545)	1.051** (0.490)	0.155 (0.348)	-0.059 (0.258)	0.198 (0.309)
log(R&D Firm) <sub>t-1</sub>	-0.154*** (0.053)			-0.163*** (0.053)			-0.007 (0.014)		
GDP Growth X log(R&D Firm) <sub>t-1</sub>	-0.438* (0.241)			-0.506** (0.224)			0.064 (0.102)		
log(R&D Gov) <sub>t-1</sub>	-0.012 (0.064)			-0.016 (0.064)			-0.007 (0.014)		
GDP Growth X log(R&D Gov) <sub>t-1</sub>	0.239 (0.208)			0.098 (0.204)			0.178* (0.093)		
log(R&D HES) <sub>t-1</sub>	0.036 (0.038)			0.028 (0.039)			0.014 (0.010)		
GDP Growth X log(R&D HES) <sub>t-1</sub>	-0.044 (0.212)			-0.049 (0.197)			0.069 (0.109)		
N	1691	1691	1691	1691	1691	1691	1691	1691	1691
R <sup>2</sup>	0.821	0.818	0.818	0.827	0.823	0.823	0.304	0.305	0.305
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses  
\* p<0.10, \*\* p<0.05, \*\*\* p<0.

## 6. Discussion and conclusion

External environments, such as macroeconomic conditions, shape firms' innovation activities, with university-industry collaborations often following similar patterns (Agostino and Moreno, 2019). Some scholars (e.g., Schumpeter, 1939) suggest that innovation is countercyclical, increasing during recessions. However, most empirical evidence finds that innovation activities are procyclical due to financial constraints that hinder firms' ability to sustain R&D expenditures. As a result, innovations are often delayed until more favorable economic conditions arise (Barlevy, 2007; Shleifer, 1986). However, firms may respond to economic cycles by adopting more exploratory innovation processes (Manso et al., 2023; March, 1991) and broadening their knowledge base through collaborations with universities and public research organizations. Such collaborations facilitate access to basic knowledge (Bercovitz and Feldman, 2007) and can change firms' learning processes (Gupta et al., 2006; March, 1991).

In this paper, I investigate the relationship between the business cycle and UICs, in particular whether UICs led to exploratory or exploitative innovation in period of expansions and recessions. The empirical analyses rely on the patenting activities of universities (including public research organizations) and firms, considering changes in the distribution of UICs' patenting across new and existing technology classes to disentangle the exploration and exploitation of EU NUTS-2 regions between 1990 and 2018. This paper contributes to the scarce evidence on the development of UICs and the economic cycle of EU regions over a long time period, including regional economic characteristics to control for unobserved heterogeneity. This paper also aims to improve our understanding of the role of the economic cycle on UICs and the emergence of new technologies by investigating their sensitivity to an exogenous shock that is likely to affect GDP growth and what source of R&D expenditures promotes cooperation.

The findings show that, on average, the number of patented inventions from UICs is positively correlated with the business cycles. This is consistent with other evidence on the procyclicality of firm behavior (Cincera et al., 2012; Fabrizio and Tsolmon, 2014; Manso et al., 2023). The procyclicality is driven by the emergence of technologies already patented in a region, whereas diversification of regions through the entry of new technologies is also procyclical, but to a lesser extent. Focusing on recession periods, I found that known technologies are sharply reduced in periods of recessions. In contrast, the emergence of new technologies is procyclical with periods of expansions, but is acyclical in periods of recessions, suggesting heterogeneous responses of exploratory or exploitative innovations.

Investigating the response to an economic shock, using a local projection approach à la Jordà (2005), I found that the number of patented inventions by UICs and in known technologies decreases in the first year following a negative shock but gradually increases over the subsequent 5-year horizon. These findings align closely with the long-run baseline regression results. In contrast, patented inventions in new technologies exhibit an increase after the negative shock, although no clear pattern emerges over the longer term with alternation of rise and fall.

To improve the understanding of the relationship between UICs, the diversification of regions, and the economic cycle, I focused on the moderating role of R&D expenditures by sectors. During periods of recession, the number of UICs and resulting patents in technologies known within regions appear to be positively associated with R&D performed by the private sector, but not the introduction of patents in novel technological domains. Finally, the result suggests that government R&D expenditures in periods of expansion are associated with an increase in exploratory inventions, whereas R&D performed by the private and higher education sectors is not related to the emergence of new technologies during economic expansions.

These findings also have significant policy implications. The triple helix model (Etzkowitz and Leydesdorff, 2000) highlights the central role of universities in the innovation process, emphasizing their collaborations with firms as critical for disseminating scientific knowledge and commercializing technological inventions (Cohen et al., 2002). Consequently, interest in fostering such collaborations through national and place-based policies has grown in recent decades. The results underscore the need to tailor innovation policies to the dynamics of economic cycles. While universities may face budget cuts during recessions, potentially hindering their capacity to foster collaborations, public R&D investment remains a critical driver of exploratory innovation, particularly during economic expansions. Considering the fact that the innovation process is cumulative and path-dependent nature, maintaining public R&D investment in UICs is essential for strengthening academic research commercialization and regional innovation. At the same time, the countercyclical nature of private sector R&D underscores the importance of targeted incentives, such as tax credits or grants, to support UICs during recessions when financial constraints are most pronounced for firms (Aghion et al., 2012). Policymakers should also consider the dual role of UICs in exploiting existing knowledge and exploring novel technological domains. To address firms' absorptive capacity limitations and align the divergent objectives of both innovative actors, programs that enhance ties and facilitate the transfer of basic knowledge from universities to firms are essential.

This paper is not without limitations, opening avenues for future research. First, while patents provide a useful measure of innovations, they capture only successful inventions. Moreover, UICs are not limited to patented innovations. Future research could also explore the effect of the business cycles on scientific publications implying collaboration with firms to investigate the relationship between publications and the business cycle. Another limitation relates to the fact I do not observe the characteristics of universities and firms, such as the involvement in collaborations, and the start and the end of collaborative projects that might provide more insight into the number of UICs along the business cycle. Finally, while physical proximity facilitates knowledge diffusion, collaborations among innovative actors are not entirely confined within a region (Diemer and Regan, 2022; Jaffe et al., 1993). In this analysis, I account for the ratio of intra- to inter-regional collaborations. Given that the impact of the business cycle varies across regions, collaborations with external actors from regions experiencing different economic cycles may moderate this effect. Future research could enhance our understanding of collaboration dynamics by examining relationships with neighboring and distant regions through spatial regression analyses, thereby offering deeper insights into the value of inter-regional collaborations and the direction of knowledge search. Despite these limitations, this paper contributes to the literature aiming to understand the relationship between UICs, technological diversification, and the business cycle, which has implications for the regional innovation system and economic growth.

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## Appendix

Table A. 1

Region Code		
AT11	DE72	ES43
AT12	DE73	ES51
AT13	DE80	ES52
AT21	DE91	ES53
AT22	DE92	ES61
AT31	DE93	ES62
AT32	DE94	ES63
AT33	DEA1	ES64
AT34	DEA2	ES70
BE10	DEA3	FI19
BE21	DEA4	FI1B
BE22	DEA5	FI1C
BE23	DEB1	FI1D
BE24	DEB2	FI20
BE25	DEB3	FR10
BE31	DEC0	FRB0
BE32	DED2	FRC1
BE33	DED4	FRC2
BE34	DED5	FRD1
BE35	DEE0	FRD2
BG31	DEF0	FRE1
BG32	DEG0	FRE2
BG33	DK01	FRF1
BG34	DK02	FRF2
BG41	DK03	FRF3
BG42	DK04	FRG0
CY00	DK05	FRH0
CZ01	EE00	FRI1
CZ02	EL30	FRI2
CZ03	EL41	FRI3
CZ04	EL42	FRJ1
CZ05	EL43	FRJ2
CZ06	EL51	FRK1
CZ07	EL52	FRK2
CZ08	EL53	FRL0
DE11	EL54	FRM0
DE12	EL61	HR03
DE13	EL62	HU11
DE14	EL63	HU12
DE21	EL64	HU21
DE22	EL65	HU22
DE23	ES11	HU23
DE24	ES12	HU31
DE25	ES13	HU32
DE26	ES21	HU33
DE27	ES22	IS00
DE30	ES23	ITC1
DE40	ES24	ITC2
DE50	ES30	ITC3
DE60	ES41	ITC4
DE71	ES42	ITF1
ITF2	PT11	UKJ2
ITF3	PT15	UKJ3
ITF4	PT16	UKJ4

ITF5  
ITF6  
ITG1  
ITG2  
ITH1  
ITH2  
ITH3  
ITH4  
ITH5  
ITI1  
ITI2  
ITI3  
ITI4  
LT01  
LT02  
LU00  
LV00  
ME00  
MK00  
MT00  
NL11  
NL12  
NL13  
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PL92

PT17  
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SE11  
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SK01  
SK02  
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UKC1  
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UKK1  
UKK2  
UKK3  
UKK4  
UKL1  
UKL2  
UKM5  
UKM6  
UKN0

Table A. 2 Variable Definitions

Variable	Description	Source
UIC	Number of patent applications from university-industry collaborations	OECD RegPat,
New Tech.	Number of UICs if the distribution of UIC patents across technology classes in year t represents a new entry in a given class within the prior five years	OECD RegPat, own elaboration
Known Tech.	Number of UICs if the distribution of UIC patents across technology classes in year t matches the distribution of all patents filed in the previous five years within the region	OECD RegPat, own elaboration
GDP Growth	Year-on-year natural growth rate of GDP	ARDECO
Recession	Dummy variable for negative GDP Growth	ARDECO, own elaboration
Population	Total population as of 1st January of the current year at the NUTS 2 level.	ARDECO
Stock Capital	Capital Stock at constant prices in Million EUR2015 ( $K_{t-1} + GFCF_t - CFC_t$ )	ARDECO
Total R&D	All sectors intramural expenditure in R&D, euro per inhabitant	QoG
Government R&D	Government sector intramural expenditure in R&D, euro per inhabitant	QoG
Firm R&D	Business enterprise sector intramural expenditure in R&D, euro per inhabitant	QoG
Higher Education R&D	Higher education sector intramural expenditure in R&D, euro per inhabitant	QoG
Patent	Total number of patent applications, excluding UIC	OECD RegPat
RIC	Ratio of the number intra-regional collaborations to the number of inter-regional collaborations	OECD RegPat, own elaboration
RDens	Regional average value of the sum of relatedness values of the technologies in the region to the potential entering technology divided by the sum of relatedness values of all technologies to this potential new technology class.	OECD RegPat, own elaboration

Table A. 3 Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) log(UIC)	1.000										
(2) log(Know Tech.)	0.995***	1.000									
(3) log(New Tech.)	0.443***	0.370***	1.000								
(4) GDP Growth	-0.070***	-0.071***	-0.031**	1.000							
(5) log(Population) <sub>t-1</sub>	0.453***	0.450***	0.176***	0.015	1.000						
(6) log(Pop. Density) <sub>t-1</sub>	0.321***	0.323***	0.062***	-0.018	0.298***	1.000					
(7) log(Stock Capital) <sub>t-1</sub>	0.593***	0.592***	0.209***	-0.099***	0.693***	0.301***	1.000				
(8) log(R&D) <sub>t-1</sub>	0.510***	0.511***	0.151***	-0.101***	0.168***	0.266***	0.703***	1.000			
(9) log(Patent) <sub>t-1</sub>	0.632***	0.633***	0.186***	-0.078***	0.512***	0.330***	0.815***	0.785***	1.000		
(10) RIC <sub>t-1</sub>	0.134***	0.133***	0.067***	-0.022	0.151***	0.057***	0.192***	0.129***	0.204***	1.000	
(11) RDens <sub>t-1</sub>	0.067***	0.076***	-0.060***	0.010	0.018	-0.035**	-0.247***	-0.250***	-0.119***	-0.066***	1.000

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table A. 4 Alternative Dependent Variable Transformation

Dep. Var.	asinh(UIC)	asinh(Known Tech.)	log(Known Tech.)	asinh(New Tech.)	log(New Tech.)
	(1)	(2)	(3)	(4)	(5)
GDP Growth <sub>t</sub>	1.249*** (0.364)	1.210*** (0.342)	0.559*** (0.197)	0.305* (0.155)	0.961*** (0.278)
log(Population) <sub>t-1</sub>	1.569** (0.660)	1.592** (0.664)	0.927*** (0.339)	0.291* (0.155)	1.307** (0.545)
log(Stock Capital) <sub>t-1</sub>	-0.836*** (0.215)	-0.835*** (0.218)	-0.312*** (0.106)	-0.093** (0.044)	-0.585*** (0.166)
log(R&D) <sub>t-1</sub>	-0.148** (0.065)	-0.159** (0.065)	-0.075** (0.033)	-0.000 (0.016)	-0.117** (0.050)
log(Patent) <sub>t-1</sub>	0.116*** (0.038)	0.105*** (0.037)	0.055*** (0.019)	0.026** (0.011)	0.058** (0.028)
RIC <sub>t-1</sub>	-0.982 (0.775)	-0.925 (0.748)	-0.007 (0.423)	-0.145 (0.211)	-1.239** (0.511)
RDens <sub>t-1</sub>	0.012 (0.008)	0.013 (0.008)	0.004 (0.004)	-0.001 (0.001)	0.009 (0.006)
Constant	-11.992 (9.974)	-12.311 (10.104)	-9.329* (5.052)	-3.076 (2.134)	-11.200 (8.066)
N	3231	3231	2890	3231	3231
R <sup>2</sup>	0.795	0.802	0.673	0.239	0.786
Region FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Table A. 5 Influence of Control Variables

Dep. Var.	log(UIC)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP Growth	1.066*** (0.291)	1.143*** (0.292)	0.930*** (0.298)	0.911*** (0.294)	0.796*** (0.289)	1.102*** (0.299)	1.022*** (0.292)
log(Population) <sub>t-1</sub>		1.040* (0.575)	1.440** (0.562)	1.277** (0.567)	1.401** (0.573)	1.576** (0.627)	1.388** (0.559)
log(Stock Capital) <sub>t-1</sub>			- 0.694*** (0.143)	- 0.573*** (0.150)	- 0.712*** (0.155)	- 0.731*** (0.176)	- 0.660*** (0.176)
log(R&D) <sub>t-1</sub>				-0.087* (0.044)	-0.101** (0.043)	-0.116** (0.055)	-0.124** (0.054)
log(Patent) <sub>t-1</sub>					0.098*** (0.026)	0.109*** (0.028)	0.090*** (0.031)
RIC <sub>t-1</sub>						-0.899 (0.592)	-0.839 (0.607)
RDens <sub>t-1</sub>							0.010 (0.007)
Constant	0.586*** (0.005)	-14.121* (8.130)	-11.967 (8.179)	-10.585 (8.195)	-11.066 (8.188)	-13.240 (9.194)	-11.541 (8.398)
N	4109	4109	3629	3629	3629	3231	3231
R <sup>2</sup>	0.781	0.783	0.788	0.789	0.791	0.796	0.799
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Table A. 6 Influence of Control Variables

Dep. Var.	log(Know Tech.)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP Growth	1.013*** (0.278)	1.093*** (0.279)	0.899*** (0.286)	0.878*** (0.281)	0.771*** (0.275)	1.074*** (0.282)	0.987*** (0.275)
log(Population) <sub>t-1</sub>		1.071* (0.583)	1.485*** (0.568)	1.311** (0.572)	1.426** (0.580)	1.605** (0.634)	1.400** (0.562)
log(Stock Capital) <sub>t-1</sub>			-0.712*** (0.146)	-0.583*** (0.153)	-0.712*** (0.158)	-0.736*** (0.178)	-0.659*** (0.178)
log(R&D) <sub>t-1</sub>				-0.092** (0.043)	-0.106** (0.043)	-0.123** (0.055)	-0.131** (0.053)
log(Patent) <sub>t-1</sub>					0.091*** (0.026)	0.102*** (0.027)	0.082*** (0.030)
RIC <sub>t-1</sub>						-0.858 (0.568)	-0.792 (0.585)
RDens <sub>t-1</sub>							0.011 (0.007)
Constant	0.556*** (0.005)	-14.577* (8.244)	-12.429 (8.294)	-10.954 (8.304)	-11.401 (8.313)	-13.580 (9.317)	-11.727 (8.474)
N	4109	4109	3629	3629	3629	3231	3231
R <sup>2</sup>	0.785	0.787	0.794	0.794	0.796	0.802	0.805
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Table A. 7 Influence of Control Variables

Dep. Var.	log(New Tech.)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP Growth	0.203** (0.100)	0.214** (0.100)	0.186* (0.107)	0.186* (0.107)	0.164 (0.106)	0.226* (0.124)	0.230* (0.123)
log(Population) <sub>t-1</sub>		0.145 (0.097)	0.172* (0.102)	0.173* (0.105)	0.197* (0.104)	0.219* (0.121)	0.228* (0.123)
log(Stock Capital) <sub>t-1</sub>			-0.056** (0.027)	-0.057* (0.030)	-0.083*** (0.030)	-0.072** (0.035)	-0.076** (0.036)
log(R&D) <sub>t-1</sub>				0.001 (0.010)	-0.002 (0.010)	-0.001 (0.012)	-0.000 (0.012)
log(Patent) <sub>t-1</sub>					0.019*** (0.007)	0.020** (0.008)	0.021** (0.008)
RIC <sub>t-1</sub>						-0.130 (0.168)	-0.133 (0.167)
RDens <sub>t-1</sub>							-0.000 (0.001)
Constant	0.067*** (0.002)	-1.988 (1.377)	-1.736 (1.397)	-1.749 (1.420)	-1.840 (1.413)	-2.287 (1.680)	-2.372 (1.704)
N	4109	4109	3629	3629	3629	3231	3231
R <sup>2</sup>	0.244	0.245	0.251	0.251	0.252	0.246	0.246
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Table A. 8 Alternative Control Variables

Dep. Var.	log(UIC)	log(Known Tech.)	log(New Tech.)
	(1)	(2)	(3)
GDP Growth	1.071*** (0.310)	0.992*** (0.288)	0.294** (0.131)
log(Pop. Density) $t-1$	0.639 (2.276)	0.424 (2.258)	0.727 (0.529)
log(Pop. Density) <sup>2</sup> $t-1$	0.127 (0.239)	0.153 (0.236)	-0.050 (0.053)
log(Stock Capital) $t-1$	-0.817*** (0.163)	-0.820*** (0.164)	-0.095*** (0.036)
log(Emp. R&D) $t-1$	-0.204*** (0.072)	-0.219*** (0.071)	-0.007 (0.018)
log(Patent) $t-1$	0.097*** (0.032)	0.089*** (0.031)	0.022** (0.009)
RIC $t-1$	-0.878 (0.633)	-0.809 (0.596)	-0.145 (0.203)
RDens $t-1$	0.009 (0.007)	0.010 (0.007)	-0.000 (0.001)
Constant	4.745 (5.590)	5.294 (5.579)	-1.167 (1.305)
N	3054	3054	3054
R <sup>2</sup>	0.807	0.814	0.250
Region FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes

Standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table A. 9 Controlling for two-year lags

Dep. Var.	log(UIC) (1)	log(Known Tech.) (2)	log(New Tech.) (3)
GDP Growth	1.028*** (0.346)	0.974*** (0.337)	0.308* (0.158)
log(Population) <sub>t-1</sub>	0.958 (3.011)	1.428 (2.994)	-0.209 (0.894)
log(Stock Capital) <sub>t-1</sub>	-0.790 (0.559)	-0.707 (0.527)	-0.271 (0.208)
log(R&D) <sub>t-1</sub>	-0.056 (0.049)	-0.046 (0.047)	-0.013 (0.019)
log(Patent) <sub>t-1</sub>	0.034 (0.026)	0.036 (0.026)	0.003 (0.009)
RIC <sub>t-1</sub>	-0.288 (0.644)	-0.189 (0.612)	-0.156 (0.283)
RDens <sub>t-1</sub>	0.009 (0.008)	0.009 (0.008)	0.003 (0.003)
GDP Growth <sub>t-1</sub>	0.639** (0.310)	0.566* (0.288)	0.292** (0.139)
log(Population) <sub>t-2</sub>	0.308 (3.047)	-0.122 (3.058)	0.342 (0.887)
log(Stock Capital) <sub>t-2</sub>	0.070 (0.559)	0.024 (0.530)	0.113 (0.208)
log(R&D) <sub>t-2</sub>	-0.044 (0.053)	-0.072 (0.050)	0.022 (0.020)
log(Patent) <sub>t-2</sub>	0.055 (0.035)	0.046 (0.036)	0.013 (0.009)
RIC <sub>t-2</sub>	-1.191* (0.673)	-1.282* (0.699)	-0.006 (0.320)
RDens <sub>t-2</sub>	0.008 (0.009)	0.010 (0.009)	-0.002 (0.003)
Constant	-9.535 (9.280)	-10.461 (9.423)	-0.141 (1.762)
N	2209	2209	2209
R <sup>2</sup>	0.821	0.827	0.274
Region FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Table A. 10 Excluding region-year without UIC

Dep. Var.	log(UIC)	log(Known Tech.)	log(New Tech.)
	(1)	(2)	(3)
GDP Growth	1.866*** (0.510)	1.826*** (0.470)	0.491* (0.283)
log(Population) <sub>t-1</sub>	2.125*** (0.775)	2.118*** (0.751)	0.508* (0.274)
log(Stock Capital) <sub>t-1</sub>	-0.127 (0.235)	-0.066 (0.236)	-0.116 (0.080)
log(R&D) <sub>t-1</sub>	-0.134 (0.087)	-0.129 (0.086)	-0.019 (0.030)
log(Patent) <sub>t-1</sub>	0.083 (0.093)	0.094 (0.089)	0.018 (0.025)
RIC <sub>t-1</sub>	0.163 (0.715)	0.212 (0.728)	-0.058 (0.265)
RDens <sub>t-1</sub>	0.016 (0.014)	0.018 (0.014)	-0.001 (0.002)
Constant	-28.204** (11.243)	-29.013*** (10.886)	-5.804 (3.904)
N	1894	1894	1894
R <sup>2</sup>	0.785	0.798	0.232
Region FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01

Table A. 11 Excluding region-year at the 95th percentile of UIC distribution

Dep. Var.	log(UIC)	log(Known Tech.)	log(New Tech.)
	(1)	(2)	(3)
GDP Growth	0.750*** (0.250)	0.717*** (0.229)	0.134 (0.110)
log(Population) <sub>t-1</sub>	0.418 (0.323)	0.412 (0.325)	0.098 (0.092)
log(Stock Capital) <sub>t-1</sub>	-0.509*** (0.132)	-0.508*** (0.132)	-0.042 (0.030)
log(R&D) <sub>t-1</sub>	-0.091** (0.043)	-0.096** (0.041)	-0.000 (0.011)
log(Patent) <sub>t-1</sub>	0.084*** (0.024)	0.076*** (0.023)	0.018** (0.007)
RIC <sub>t-1</sub>	-0.557 (0.577)	-0.498 (0.553)	-0.121 (0.176)
RDens <sub>t-1</sub>	0.005 (0.004)	0.006 (0.004)	-0.001** (0.000)
Constant	0.353 (4.965)	0.417 (5.068)	-0.880 (1.278)
N	3036	3036	3036
R <sup>2</sup>	0.707	0.716	0.211
Region FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes

Standard errors in parentheses

\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01