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RESEARCH

Fostering regional entrepreneurial ecosystem development: the role of science and technology park networks

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Abstract
Science and Technology Parks (STPs) are recognized as key drivers of regional development, although their relationship with regional entrepreneurial ecosystems (EEs) remains underexplored, particularly in terms of longitudinal and comparative analyses. This study addresses these gaps by examining how participation in a global STP network impacts regional EE development. Using a longitudinal dataset on STPs' entry and exit dynamics in the International Association of Science and Technology Parks and Areas of Innovation (IASP) across multiple European regions, we analyze the effects of joining a global STP network on key EE dimensions. To do so, we apply a non-parametric generalization of the difference-in-differences estimator for time-series cross-sectional data. The results reveal that joining IASP strengthens the intermediary dimension of regional EEs where parks are located, facilitating talent attraction and enhancing cross-regional knowledge spillovers. These effects are both immediate and context-dependent, with more pronounced impacts observed in regions with lower GDP per capita and outside the European Union. Theoretically, the study advances the STP literature by adopting a dynamic, macro-regional perspective, extending micro-level findings and linking STPs' increased R&D efficiency to international collaboration. Additionally, it bridges STP and EE literatures, emphasizing the role of STPs as catalysts of regional EE development. Practically, our findings provide insights for policymakers and STP managers, highlighting the importance of supporting not only the creation of STPs but also their participation in global networks to foster innovation, especially in regions with fragmented or underdeveloped policy frameworks.

Keywords Science and technology park · Entrepreneurial ecosystem · Regional development · Global network · Intermediary services · Impact evaluation

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1 Introduction

An increasingly growing number of countries have implemented Science and Technology Parks (STPs) to develop and revitalize regions, boost high-tech industry sectors, foster greater industry-academia interaction, support new technology-based firms, and encourage academic spin-offs (Henriques et al., 2018). In this view, the multifaceted benefits of STPs can be summarized within two categories: i) the benefits they provide to tenant firms and ii) the benefits they provide to local economies (Guadix et al., 2016). On the one hand, academic research has extensively shown that firms within STPs outperform off-park firms in terms of patenting activity, research and development (R&D) investment, job creation rates, and collaboration with universities (Siegel et al., 2003; Squicciarini, 2008; Ubeda et al., 2019; Yang et al., 2009). On the other hand, there is broad consensus that STPs serve as regional innovation policy tools, enhancing innovation capacity and promoting regional development (Albahari et al., 2023; Jacobsen et al., 2024; Zhang & Wu, 2012). In both contexts, STPs act as intermediary actors, stimulating and managing knowledge flows among key stakeholders (IASP, 2025).

Traditionally, the discourse surrounding STPs' functioning and organization has adopted a regional innovation system perspective to analyze simultaneously the complex interplay between tenant firms and their impact on regional development (Rip, 2002; Zhu & Tann, 2005). However, the representation, analysis, and role of STPs in shaping regional outcomes are progressively shifting toward the adoption of an entrepreneurial lens (Löfsten et al., 2020). In particular, more recent studies have recognized STPs as essential actors and components of entrepreneurial ecosystems (EEs) (Kanda et al., 2025; Mohammadi et al., 2025). The popularity of EEs has indeed dramatically increased in the past decade (Cao & Shi, 2021; Stam, 2015). Differently from other ecosystem types, EEs are inherently linked to regional development and economic growth (Acs et al., 2018; Hakala et al., 2020), contributing to local economic development by fostering productive entrepreneurship (Audretsch & Belitski, 2021). This shift in the landscape has led policymakers and governments to consider STP actors as crucial elements in enhancing regional competitiveness and contributing to the creation of EEs (Cumming et al., 2019; Theeranattapong et al., 2021).

Despite the abovementioned streams, the literature on STPs presents relevant gaps. Notably, most studies offer a static view of STPs, failing to capture the dynamic nature of these parks (Lecluyse et al., 2019). Indeed, the lack of longitudinal data has been identified as a significant barrier to advancing knowledge in the field of STPs (Albahari et al., 2023; Audretsch & Belitski, 2019). Moreover, comparative studies analyzing multiple STPs on a large scale remain scarce, limiting our understanding of their impact across different geographical contexts (Lopes et al., 2025; Sandoval Hamón et al., 2024). In particular, despite their growing relevance, the role of STPs in fostering regional EE growth remains underexplored (Germain et al., 2023) compared to other intermediary organizations, including incubators, accelerators, and universities (e.g., Fuster et al., 2019; Pustovrh et al., 2020; Roundy et al., 2017). As a consequence, while previous research has examined how participation within STPs influences tenants' innovation performance, networking, and intermediation mechanisms at the micro-level (Albahari et al., 2023; Koçak & Can, 2014; Laspia et al., 2021), little attention has been paid to how and whether STPs' networking and intermediation mechanisms are exerted at the macro-level. In this context, collaboration among STPs and key relevant stakeholders has been demonstrated to enhance talent acquisition and, consequently, STPs' success (Cadorin et al., 2021), whereas the effect of the STP networks – or associations – on regional development remains largely underinvestigated. These gaps highlight the need for a more dynamic and comprehensive exploration of how STP networks can contribute to the development of regional EEs. To this aim, the following research questions are proposed: (i) "Do STP networks affect regional EE development?" and (ii) "What EE dimensions are impacted by participation in STP networks, and when does the effect become observable?".

To address our research questions, we propose a multi-stage approach focusing on the largest global STP network: the International Association of Science and Technology Parks and Areas of Innovation (IASP). Specifically, we obtained access to data on STPs' entry and exit dynamics, enabling us to assess whether participation in IASP affects the regional EE in which a park is embedded through a longitudinal analysis spanning multiple countries. As a first step, we conducted an expert interview with the Knowledge and Project Manager of IASP to gain insights into the association's membership mechanisms and selection criteria. During the interview, we presented EE dimensions as defined by Stam (2015) and operationalized by Leendertse et al. (2022), namely: formal institutions, culture, network, physical infrastructure, finance, leadership, talent, knowledge, intermediary services, and demand. This discussion strengthened the conceptual focus on the regional EE dimensions potentially affected by the entry of STPs into the IASP global network, integrating insights from the literature review and highlighting their role in promoting knowledge exchange as well as the development of intermediary and support services. However, all EE dimensions were incorporated into our empirical analysis to ensure a comprehensive and balanced assessment of the broader ecosystem. We then collected data to monitor regional EE dimensions over time and assess their relationship with STPs' participation in IASP. For the analysis, we employed a non-parametric generalization of the difference-in-differences (DiD) estimator for time-series cross-sectional (TSCS) data. This method overcomes the limitations of previously introduced DiD estimators (e.g., Callaway & Sant'Anna, 2021) and synthetic control methods (Abadie et al., 2010), as it (i) does not rely on parametric assumptions, (ii) does not require a long pre-treatment period for constructing control units, and (iii) is particularly suitable when the number of treated units is small (Imai et al., 2023).

Our findings indicate that STP participation in global networks contributes to strengthening the intermediary services of regional EEs, fostering collaborative R&D activities beyond regional boundaries. These effects are typically immediate, taking place in the year of entry into IASP, and exhibit heterogeneous patterns depending on the regions' GDP per capita level and EU membership status. Overall, the results suggest that global STP networks can act as complementary mechanisms for talent attraction and cross-border collaboration, particularly in regions lacking cohesive policy frameworks – such as European countries outside the EU – thus reinforcing their role in regional economic development.

The remainder of the paper is organized as follows. An overview of the state of the art on STPs and EEs is provided in Sect. 2. Section 3 presents our multi-stage approach, starting with the description of the case study, followed by the introduction to our methodology and data selection. Finally, the results are reported and discussed in Sect. 4, while Sect. 5 highlights the main theoretical and practical contributions, as well as possible limitations and further developments of this work.

2 Literature review

In this section, we provide a comprehensive review of the literature on STPs and their impact on regional innovation systems. Then, we introduce the concept of EEs, grounded in regional development and strategic management literatures. In particular, we examine the role of intermediary actors and identify key contributions that bridge these two research streams, highlighting critical gaps concerning the role of STPs in regional EE development.

2.1 Science and technology parks as a policy for regional development

STPs have evolved over time, with various terms such as "research park," "technology park," "science and technology industrial park," "high technology development," "innovation center," and "technology incubator" often used interchangeably (Zhang, 2005). This conceptual complexity has led to diverse interpretations, influenced by the constellation of the actors populating these systems. A widely accepted definition from IASP has been employed by several scholars in the economic field to assess the role, organization, and purpose of the different stakeholders at all levels (Bellavista & Sanz, 2009; Cadorin et al., 2021; Etzkowitz & Zhou, 2018; Lecluyse et al., 2019). In this view, STPs are described as "organizations managed by specialized professionals with the primary aim of fostering innovation, enhancing the competitiveness of associated businesses and knowledge institutions, and ultimately increasing the wealth of the surrounding community" (IASP, 2025). Based on this definition, the primary reasons for the existence of STPs are the benefits they provide to tenant firms and local economies (Guadix et al., 2016). STPs have indeed increasingly become key instruments for business innovation and economic development, particularly due to their ability to coordinate agents involved in micro- and macro-level processes within network-based innovation systems (Bellavista & Sanz, 2009).

At the micro-level, the academic debate have focused on evaluating the returns to firm of on-park location, in relation to their economic and innovation performance, as well as patterns of cooperation (Albahari et al., 2023). A distinctive feature of STPs is their effort to facilitate networking by selecting a set of tenants that may find reasons to interact, and by directly brokering ties among these firms (Koçak & Can, 2014). In particular, STPs serve as intermediaries through varying agreements, from basic framework contracts to more integrated partnerships (Laspia et al., 2021). They typically act as innovation intermediaries for university-industry collaboration, balancing aspirations for knowledge-based development with the challenge of limited resources (Etzkowitz & Zhou, 2018; Phongthiya et al., 2022). In this vein, STPs foster knowledge spillovers and generate positive externalities for tenant firms (Díez-Vial & Montoro-Sánchez, 2016; Montoro-Sánchez et al., 2011). However, the extent of these benefits may vary across contexts. Firms with an intermediate or high absorptive capacity are more likely to leverage the networks and services provided by an STP, thus enhancing their innovation performance (Ubeda et al., 2019).

Interesting insights are provided by studies comparing firms inside and outside STPs to analyze the effects induced by participating in the park. Historically, scholars showed that firms within STPs tend to perform better than those outside, particularly in terms of patenting activity (Siegel et al., 2003; Squicciarini, 2008). In this context, it has been shown that technology-based firms located within STPs tend to invest significantly more efficiently than their counterparts outside these environments (Yang et al., 2009). Notably, younger firms tend to benefit more from being located within STPs than older ones in terms of patent quality, and a similar result holds for larger firms compared to smaller ones (Anton-Tejon et al., 2024). Additionally, firms inside STPs typically establish stronger links with universities and exhibit higher job creation rates, possibly due to supportive policies and incentives (Löfsten et al., 2020). While it was largely shown how STPs strengthen collaborations with universities and research centers enhancing knowledge flows and transfer among actors (Díez-Vial and Fernández-Olmos, 2015; Ng et al., 2022), STPs promoted by universities do not seem to perform better (Anton-Tejon et al., 2024).

Moving to the meso-level, STPs have been analyzed as instruments of regional innovation policy, as they foster collaboration and strengthen regional networks (Jacobsen et al., 2024). Over the past decades, national and regional governments have increasingly invested in STPs as key tools to drive technological advancement and economic growth (Albahari et al., 2023; Minguillo et al., 2015). Such investments have proven effective in enhancing regional innovation capacity by improving and exploiting the full potential of university–industry relationships (Olcay & Bulu, 2018). Moreover, public investments in the creation and development of STPs have been shown to generate a virtuous cycle, attracting greater foreign direct investment and strengthening competitiveness (Zeng et al., 2011). In these contexts, STPs represent "top-down short cuts to create a Silicon Valley-like high-tech conurbation," i.e., attractive environments for both R&D units of firms and government agencies (Etzkowitz & Zhou, 2018).

While these local initiatives have traditionally focused on fostering regional development, the emergence of global STP networks has expanded their scope beyond territorial boundaries, associated with greater impact and enhanced innovation capabilities, although a clear understanding of how and why they generate added value for the ecosystem is still lacking (Hrebennyk et al., 2024). In this vein, the concept of regional innovation system has gained popularity given its link with both regional competitiveness and innovation activities and processes (López-Rubio et al., 2020). In the last decades, the discourse on STPs has often adopted the regional innovation system perspective to analyze the complex interplay between universities and industries and its impact on regional development (Theeranattapong et al., 2021; Zhu & Tann, 2005). However, the debate has increasingly shifted toward an entrepreneurial lens to investigate the role of STPs in shaping regional outcomes (Löfsten et al., 2020), laying the groundwork for integrating STPs in the discourse on EEs.

2.2 Intermediary actors in entrepreneurial ecosystem research

The concept of EEs has gained significant attention over the past decade (Cao & Shi, 2021), evolving rapidly and generating greater enthusiasm than previous frameworks, such as entrepreneurial systems, particularly within policy discourse (Alvedalen & Boschma, 2017; Brown & Mawson, 2019). The EE approach emerged in response to the need for fostering supportive environments for regional development, enabling high-growth firms to thrive (Mason & Brown, 2014). Given this strong regional connection, cultural and social norms, along with internal market dynamics, contribute to interregional differences in the prevalence of high-growth firms (Corrente et al., 2019) and the emergence of knowledge-intensive business service areas (Horváth & Rabetino, 2019).

Differently from other ecosystem types – such as business, innovation, digital, and knowledge ecosystems – EEs are intrinsically linked to regional development and economic growth (Acs et al., 2018; Hakala et al., 2020). Specifically, EEs contribute to regional economic development by fostering productive entrepreneurship, particularly in regions with a strong presence of the creative class and creative industries (Audretsch & Belitski, 2021). EEs, therefore, evolve through the processes of entrepreneurial opportunity discovery and pursuit (Autio et al., 2018), as well as through the accessibility of regional resources, often shaped by government interventions (Spigel & Harrison, 2018). The idea that economic transformation unfolds unevenly across EEs, driven by geographically specific mechanisms, is central to evolutionary economic geography (Boschma & Martin, 2007). This perspective has been widely applied to the study of regional innovation systems and clusters (Hassink et al., 2014), further leading to the adoption of the regional lens in EE research.

Such embeddedness in regional economic, technological, and societal contexts (Audretsch et al., 2019) is reflected in the multidimensional nature of EEs, which typically integrate financial, knowledge, institutional, and social components (Nicotra et al., 2018; Spigel, 2017). Isenberg (2011) and Stam (2015) were among the first to conceptualize this multifaceted structure within foundational models for mapping EE dimensions. Specifically, Isenberg (2011)'s framework identifies six fundamental pillars of EEs: finance, policy, culture, markets, human capital, and support mechanisms. These domains partially overlap with those introduced later by Stam (2015) and refined in Stam and Van de Ven (2021), who propose a model linking ten EE elements to productive entrepreneurship outcomes: formal institutions, culture, network, physical infrastructure, finance, leadership, talent, knowledge, intermediary services, and demand. These elements have been operationalized by Leendertse et al. (2022) into a set of measurable indicators at different geographical scales, now serving as the predominant framework in EE research for monitoring and assessing EE development in Europe.

It follows that EEs are inherently complex systems, characterized by a relational nature grounded in ecological systems theory (Acs et al., 2017). Within these systems, actors interact through networks of knowledge, labor, and social capital (Malecki, 2018), which collectively shape the network-based structure of EEs (Ancona et al., 2023; Cavallo et al., 2021; Neumeyer et al., 2019). In this vein, the interrelatedness among cognitive, organizational, social, institutional, and geographical proximities is essential to facilitate interactions among ecosystem actors and enable the formation of viable ecosystems (Yamamura & Lassalle, 2020). Frequent interactions are indeed at the core of EEs, ensuring that resources are more readily accessible to all actors (Feld, 2012).

The distribution of resources within EEs is mediated by intermediary organizations, such as incubators, accelerators, and universities, which play a crucial role in coordinating knowledge flows, facilitating access to venture capital, and fostering regional economic growth (Fuster et al., 2019; Pustovrh et al., 2020; Roundy, 2017). Specifically, incubators are pivotal to strengthen network ties among startups and between startups and investors, shaping the collaborative structure of EEs according to different levels of dependence (Hernández-Chea et al., 2021; van Rijnsoever, 2020). Accelerators, in turn, act as catalysts for the development of startup infrastructures within entrepreneurial clusters (Bliemel et al., 2019). This meso-level intermediary role enhances the commitment of actors to the EE by promoting cooperation and knowledge sharing practices (Goswami et al., 2018; Pustovrh et al., 2020). In addition to providing technical knowledge ("know-what") and practical expertise ("know-how"), accelerators facilitate access to crucial entrepreneurial networks ("know-who"), which are central in entrepreneurial learning experiences (Seet et al., 2018).

In this way, accelerator programs strengthen startup embeddedness within EEs, emerging as one of the key platforms to channel venture capital and investor flows (Dalle et al., 2023). These dynamics increase the availability of innovation resources within regional EEs, attracting other key players, such as university spin-offs, seeking proximity to other firms and entrepreneurial actors (Rossi et al., 2023). As a result, universities also play a critical role in regional EE development (Fuster et al., 2019), along with spin-out companies burgeoning from multinational enterprise employees that become incubators for new waves of entrepreneurs (Ryan et al., 2021).

2.3 Science and technology parks and regional entrepreneurial ecosystems

Among institutional actors, STPs are particularly influential in supporting the early development of academic spin-offs, strengthening the establishment of academic entrepreneurship practices within EEs (Franco-Leal et al., 2020). Entrepreneurs frequently locate their ventures near STPs and incubators to gain access to technological advancements, form alliances, and leverage shared infrastructure (Audretsch & Belitski, 2019, 2021; Cuvero et al., 2023). Moreover, STPs act as connectors with other regions, linking ecosystems in similar stages of development (Oliver et al., 2020). For this reason, both practitioners and scholars consider STPs as essential actors and components of EEs (Kanda et al., 2025; Mohammadi et al., 2025). Policymakers and governments are also increasingly looking to STPs tenants (e.g., universities or corporate firms) as crucial elements of the knowledge-based economy to foster regional competitiveness and contribute to the creation of EEs (Cumming et al., 2019; Theeranattapong et al., 2021). However, despite their crucial role in facilitating the creation of EEs through the coordination and support of different stakeholders, the contribution of STPs to regional EE growth remains underexplored compared to other intermediary organizations (Germain et al., 2023).

When considered as interconnected infrastructures rather than isolated entities, STPs may collectively contribute to the development of regional EEs. As discussed in Sect. 2.1, existing studies have extensively examined the role of individual parks and their tenant firms, showing that participation in STPs fosters innovation performance, knowledge exchange, and intermediation mechanisms among co-located actors. Extending this reasoning to the regional level, participation in broader global STP networks may further amplify these benefits. By connecting multiple STPs through shared initiatives, joint research programs, and cross-regional partnerships, such networks could enhance the accessibility of technological resources, promoting complementarities among regions with different specializations (Cadorin et al., 2021; Oliver et al., 2020). In this sense, collaboration among STPs may generate a multiplier effect, allowing the advantages produced within one park to reinforce innovation capacity elsewhere and contributing to a more cohesive and competitive ecosystem architecture. Specifically, STP networks are expected to foster the transition towards knowledge-intensive regions, contributing primarily to resource endowment components – rather than institutional arrangements – by promoting knowledge exchange and developing intermediary and support services within EEs. In this context, the temporal dimension of these processes is equally relevant. Prior research on individual STPs suggests that the benefits of participation tend to emerge progressively as relationships consolidate over time. By analogy, the outcomes of network participation are also likely to unfold gradually, depending on the institutional context and the absorptive capacity of the regions involved.

3 Research design

Through our analysis of the literature on STPs and EEs, we identified different research gaps within each field and at their intersection. These gaps led us to formulate two main research questions, as outlined in Sect. 1. To address these questions, we propose a multi-stage approach focusing on IASP, the largest global STP network. Specifically, we obtained access to data on STPs' entry and exit dynamics, enabling us to assess whether participation in IASP affects the regional EE in which a park is embedded through a longitudinal analysis spanning multiple countries.

As a first step, we conducted an expert interview with the Knowledge and Project Manager of IASP to gain insights into the association's membership mechanisms and selection criteria. During the interview, we introduced EE dimensions as defined by Stam (2015) and operationalized by Leendertse et al. (2022). This discussion helped us strengthen the conceptual focus on regional EE dimensions potentially affected by IASP membership. Afterward, we collected data to monitor regional EE dimensions over time and assess their relationship with STP participation in IASP. For this analysis, we employed a non-parametric generalization of the DiD estimator for TSCS data (Imai et al., 2023).

For clarity, our research design is summarized in Fig. 1. The specific steps of our methodological approach are detailed in Sects. 3.1 and 3.2.

3.1 Case study: the IASP global network

Since its establishment in 1984, IASP has been recognized as a leading force in fostering collaboration and driving innovation on a global scale. The organization is dedicated to facilitating connections and knowledge exchange within a dynamic international network comprising STPs, areas of innovation, and innovation districts. By coordinating an active community of stakeholders, IASP promotes synergies at both national and international levels. Today, IASP boasts a diverse and extensive membership base, with over 350 members representing more than 115, 000 companies across 80 countries. Its global presence is structured into six main regional divisions: Africa, Asia Pacific, Europe, Latin America, North America, and West Asia North Africa. In addition to its headquarters in Malaga, Spain, and

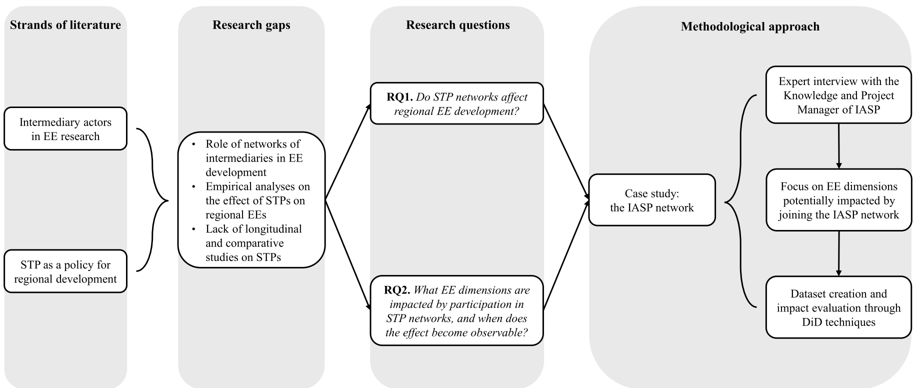


Fig. 1 Research design

a regional office in Beijing, China, the organization enhances its impact through global conferences and regional events, fostering cross-border collaboration and knowledge diffusion.

We selected the IASP global network as a case study to address our research questions for three main reasons. First, as the largest association of STPs worldwide, IASP provides a unique setting that enables analysis transcending the contextual limitations of traditional case studies. Its extensive membership network allows for investigating the role of STPs in regional EE development from multiple perspectives and across different geographical contexts, addressing current lacks of research in this regard (Germain et al., 2023). Second, the IASP's definition is widely referenced in key studies on STPs, as emphasized in Sect. 2.1, and is central to the discussion on their role in the development of regional EEs (Bellavista & Sanz, 2009; Cadorin et al., 2021; Etzkowitz & Zhou, 2018; Lecluyse et al., 2019). Third, the association granted access to a longitudinal dataset covering the period from 1985 to 2024. The availability of such data is particularly valuable, as the lack of longitudinal studies has been frequently cited as a major constraint in advancing research on STPs (Albahari et al., 2023; Audretsch & Belitski, 2019). Prior to analysis, the dataset provided by IASP was validated through data quality controls to verify completeness, internal consistency, and accuracy over time, including checks for missing values, duplicate entries, and potential inconsistencies across observations.

A summary of the IASP's characteristics is provided in Table 1.

3.1.1 The expert interview

In the initial phase of our study, we conducted an expert interview with the Knowledge and Project Manager of IASP. This interview provided critical insights into IASP's internal operations, the broader dynamics of its global network, and its strategic objectives. The interview protocol was structured around three core themes:

- Operational mechanisms of the IASP global network – Understanding how IASP facilitates connections among STPs, supports their activities, and influences their development through networking and collaboration.
- Assessment criteria and admission process for STP membership – Clarifying the stand-

Table 1 Key characteristics of the IASP case study

Attribute	Description
Year of establishment	1984
Role	Leading network in fostering collaboration among STPs
Mission	Support STPs worldwide by catalyzing innovation, fostering growth, and facilitating cross-border collaboration
Community	Science and technology parks, areas of innovation, innovation districts
Membership size	Over 350 members representing more than 115, 000 companies across 80 countries
Regional divisions	Africa, Asia Pacific, Eurasia, Europe, Latin America, North America, West Asia North Africa
Reasons for case study selection	(i) Leading and larger association of STPs; (ii) widely referenced in STP research; (iii) access to a longitudinal dataset (1985–2024)

ards STPs must meet to join IASP and the evaluation process applied to new applicants.
- Introduction of EE dimensions as defined by Stam (2015) and operationalized by Leendertse et al. (2022) – Identifying regional EE dimensions potentially impacted by joining the IASP network to ensure methodological rigor and reinforcing the integration of the STP and EE research streams within a coherent analytical framework.

Therefore, the primary objectives of the expert interview were to deepen our understanding of IASP's internal processes, the mechanisms regulating relationships among members, and, most importantly, to identify the EE dimensions that IASP membership can potentially impact. In this context, expert interviews are crucial for refining knowledge production by offering privileged access to tacit knowledge and sector-specific expertise (Meuser & Nagel, 2009).

The interview took place in April 2024, lasted approximately one hour, and was conducted in English. To ensure accuracy, it was recorded, transcribed, and translated into the authors' native language. The insights gained significantly contributed to the design of our methodological approach, leading to two key outcomes:

- Ensuring coherence in STP characteristics and robustness of identification criteria for DiD estimators. The interview provided a clearer understanding of how IASP ensures consistency across its members, following a rigorous admission process including an in-depth assessment by the Executive Board that helps maintain high-quality standards within the global network. This selection process minimizes heterogeneity across STPs, reducing biases that typically arise when analyzing different types of parks (Albahari et al., 2017). As a result, our study benefits from a more reliable framework for applying DiD techniques, as discussed in the next section.
- Strengthening the conceptual focus for assessing the impact of STP networks on regional EE development. The interview helped bridge two critical components of our research: the benefits of participating in IASP's global network and the EE dimensions most likely to be affected by IASP membership. By integrating these insights, we refined the conceptual focus of our paper enhancing the study's relevance and methodological rigor. Specifically, the interview highlighted *intermediary services* (hereafter referred to simply as "intermediaries") and *knowledge* as the most relevant EE dimensions for assessing the impact of STP membership. This aligns not only with IASP's emphasis on fostering innovation and strengthening competitiveness among businesses and knowledge institutions but also with ongoing debate on the role of STPs at the micro- and meso-levels (Díez-Vial & Montoro-Sánchez, 2016; Etzkowitz & Zhou, 2018; Ng et al., 2022; Phongthiya et al., 2022). Notably, all other EE dimensions as operationalized by Leendertse et al. (2022) are incorporated into our estimation model to ensure a comprehensive representation of the EE and to avoid any interpretative bias toward specific mechanisms of STP influence.

Overall, this process minimized potential biases and enhanced the reliability of our analytical approach.

3.2 Methodology and data

The main objective of this paper is to analyze how participation in a global network of STPs affects the development of the regional EE where a park is embedded. Therefore, our units of analysis are NUTS-2 regions hosting one (or eventually more) STPs belonging to IASP within the analyzed time window. In particular, we can benefit from an initial set of 221 STPs that joined (and, in some cases, exited) IASP between 1985 and 2024. We assess this effect by considering entrance into IASP as a treatment potentially stimulating EE dimensions, as introduced in Sect. 3.1. A popular way to estimate the effect of a policy or treatment on specific outcome variables is to compare treated and control units that share similar observed characteristics in the pre-treatment period. In our case, STPs may join IASP in different years, meaning they are subject to staggered treatments. Moreover, we assume regional EE dimensions depend on past treatments (i.e., members who joined IASP earlier). Therefore, a method accounting for dynamic effects must be employed.

To this aim, we adopt a non-parametric generalization of the DiD estimator recently developed by Imai et al. (2023), which has already been applied in economic geography studies (e.g., Celli et al., 2023), specifically for TSCS data. This type of data consists of repeated observations of the same units, which may receive the treatment multiple times, with the timing of the treatment varying across units. In general, DiD estimators compare the outcome trajectory (Y) from t_1 to t_2 between a treatment group a switching from untreated to treated and a control group b that remains untreated at both periods. Formally, DiD estimators are defined as follows:

$$DID = Y_{a,2} - Y_{a,1} - (Y_{b,2} - Y_{b,1}) \tag{1}$$

Matching methods enhance the validity of causal inference by selecting control units that resemble treated ones and provide insights into the quality of returned matches (Stuart, 2010). They help reduce the dependence of the treatment variable on observed confounders (Ho et al., 2007). Imai et al. (2023) introduced a matching method for TSCS data, addressing limitations in prior studies that relied on linear regression models with fixed effects (e.g., Angrist & Pischke, 2009) and suffered from strong parametric assumptions and difficulties in interpreting counterfactual estimates (Imai & Kim, 2021).

The methodology employed within this paper overcomes such limitations. In particular, following Imai et al. (2023), we first select for each treated region a set of control regions that are not yet treated (i.e., regions that do not yet host an IASP member at the time of comparison). We use Mahalanobis distance matching, which assigns positive weights to control units with similar trends in the pre-treatment outcome and control covariates. This method performs well when the sample size is relatively small (Zhao, 2004) and has been used in STP studies to evaluate the effect on tenant firms (Liberati et al., 2016). Notice that not-yet-treated regions serve as valid control units in the absence of purely untreated units (Callaway & Sant'Anna, 2021), as in our case. In fact, our dataset includes entry and exit dynamics of parks that joined IASP over time. This also ensures comparability in IASP selection and membership criteria. We use lagged values of GDP per capita, percentage of employment, and population density as pre-treatment covariates to ensure socio-economic and demographic similarities. Additionally, we include lagged values of all EE dimensions,[1]

[1] Except finance-related variables, which were inaccessible.

as they are interrelated (Leendertse et al., 2022). All variables employed, as well as available time spans and data sources, are listed in Table 2. By combining this set of variables with the entry and exit dynamics of STPs – aggregated at the NUTS-2 level based on their corresponding region – we obtain a set of 59 NUTS-2 regions hosting one or more STPs across 22 European countries that joined IASP between 2011 and 2024.

Then, for each treated region, we estimate the counterfactual outcome using the weighted average of three control units in the refined matched set. Different numbers of control units are tested for robustness (see Sect. 4.1). Finally, we estimate the average treatment effect among treated (ATT) by averaging the DiD estimates across all treated units.

To apply this methodology, we define F as the number of leads, representing the outcome measured F periods after treatment. We set $F = 3$ to capture the effect on the regional EE three years after an STP join IASP. Additionally, we define $L = 3$ as the number of lags, ensuring matching based on pre-treatment trends up to three years before treatment. As in the regression approach, choosing L involves a bias–variance tradeoff: higher values

Table 2 Variable selection (NUTS-2 level)

Variable	Description	Data source	Period
IASP membership	Treatment	IASP (confidential)	1985–2024
Percentage of employment in knowledge-intensive market services	EE dimension: Intermediary services	Eurostat	2008–2022
Intramural R&D expenditure as a percentage of GDP	EE dimension: Knowledge	Eurostat	2011–2021
Number of coordinators in FP7/H2020/Horizon Europe projects	EE dimension: Leadership	Cordis	2011–2022
Births of new enterprises	EE dimension: Entrepreneurship culture	Eurostat	2008–2022
Quality of Government Index	EE dimension: Formal institutions	European Commission	2010–2022
Percentage of households with access to the internet at home	EE dimension: Physical infrastructure	Eurostat	2011–2022
Percentage of population aged 25–64 that completed tertiary education	EE dimension: Talent	Eurostat	2011–2022
Disposable income of private households	EE dimension: Demand	Eurostat	2012–2022
Innovative SMEs collaborating with others	EE dimension: Networks	European Innovation Survey	2016–2022
Population density	Demographic context	Eurostat	2011–2022
GDP per capita	Socio-economic context	Eurostat	2011–2022
Employment rate	Socio-economic context	Eurostat	2011–2022

enhance the unconfoundedness assumption (i.e., the credibility of the matching) but reduce the number of potential matches, affecting estimate efficiency. In our case, setting $L = 3$ results in a final dataset for our main analysis comprising 48 NUTS-2 regions across 19 European countries. Since the choice of L is arbitrary, we conduct robustness checks by varying it in Sect. 4.1. Once these parameters are defined, we compute the DiD estimate of the ATT for all treated units.

While this approach relies on a weaker set of assumptions compared to common methodologies for analyzing TSCS data (Imai et al., 2023), it still requires some conditions to be verified. First, the parallel trend assumption after conditioning on the treatment, outcome and covariate histories must hold. This methodology has advantages over traditional regression approaches, as it allows for testing the parallel trend assumption directly from the resulting covariate balance between treated and matched control units. Therefore, once the matched sets are determined and refined, it is immediately possible to examine whether the treated and matched control units are comparable with respect to observed confounders. Second, while the methodology accounts for some carryover effects (i.e. the possibility that past treatments influence future outcomes), it assumes no interference between regions, meaning that the potential outcome of region i at time $t + F$ does not depend on the treatment status of other regions. This assumption is reasonable, as prior research has employed similar time spans to ours to estimate the effects of knowledge spillovers at the micro-level (Díez-Vial & Fernández-Olmos, 2015). Thus, we consider STP spillover effects unlikely to extend beyond regional boundaries, and, whether happening, they would require a longer time to exhibit.

The complete list of regions – including the number of STPs and the years of treatment – together with the mathematical formulation of the DiD estimator proposed by Imai et al. (2023), is provided in Online Appendix A.

4 Results

Following the approach outlined in Sect. 3, we estimate the effects of STP networks on the intermediaries and knowledge dimensions of regional EEs. Our main specifications include all available variables for 48 NUTS-2 regions over a sufficiently long time window, allowing us to consider the number of lags and leads, as defined in Sect. 3.2. Specifically, when analyzing the impact on intermediaries, we include population density, employment rate, and GDP per capita as covariates from 2011–2022, along with the following EE dimensions available within the same time span: talent, institutions, infrastructure, entrepreneurship culture, and leadership. Similarly, when examining the impact on knowledge, we control for employment rate and GDP per capita from 2011–2021, as well as intermediaries, talent, institutions, infrastructure, entrepreneurship culture, and leadership within the same time span. All EE dimensions are operationalized as specified in Table 2.

For completeness, we also conducted additional analyses using other EE dimensions as outcome variables (reported in Online Appendix B). However, these yielded no significant results, reinforcing the validity of the insights derived from the literature review and expert interview.

Before presenting our main estimates, we assess covariate balance between treated and matched control units in Fig. 2. As discussed in Sect. 3.2, this test is fundamental to verify the parallel trend assumption when employing the non-parametric generalization of the DiD estimator (Imai et al., 2023), thereby strengthening the robustness of our empirical analysis. The plots indicate that all employed variables in both specifications remain stable over the three-year pre-treatment period within the standard deviation range of $(-0.5, 0.5)$, except for a slight imbalance in knowledge at $t-3$. These results suggest that the lagged values of both dependent variables and all covariates are well balanced between treated and control regions before treatment. This balance supports the plausibility of the parallel trend assumption after conditioning on treatment, outcome, and covariate histories, allowing us to attribute observed post-treatment differences causally to STPs' entry into IASP.

Figure 3 shows the estimated ATT for intermediaries and knowledge. In particular, the y-axis represents changes in the respective dimensions. Since both dependent variables are expressed as percentages, the estimated effects should be interpreted as direct percentage increases or decreases in (i) employment in knowledge-intensive market services and (ii) intramural R&D expenditure as percentage of GDP.

As it is possible to notice, STPs' entry into IASP leads to a statistically significant increase in employment in knowledge-intensive market services by 0.30 and 0.43 percentage points in the year of treatment and the following year, respectively, within the regions hosting the newly affiliated STPs ($p < 0.05$). While the effect remains positive over the entire post-entry period, it loses statistical significance beyond the first year. This result suggests that STP networks contribute to the development of intermediary services in the regional EE where STPs operate. Specifically, this effect can be attributed to enhanced expertise, know-how, and networking capabilities of tenant firms, which benefit from being embedded not only in an STP but within a broader network of STPs. This network effect may generate positive spillovers at the regional level.

In contrast, a distinct pattern emerges for intramural R&D expenditure, which shows a steady decline from the year of treatment until the third year post-entry, although the effect remains not statistically significant. The lack of significance is likely due to the smaller number of treated units in this specification (eight regions) compared to the analysis of intermediaries as the outcome variable (seventeen treated regions), given the shorter time window for data availability. Despite this limitation, the observed decline in this variable may be cautiously interpreted as consistent with the expected effects of joining an international network of STPs, which facilitates cross-border knowledge exchange and collaboration. Rather than indicating a negative impact of STP networks on knowledge-related EE dimensions, this trend aligns with the nature of the knowledge metric used in this study (and defined by Leendertse et al., 2022). Whether reaching statistical significance, the results would suggest that regions hosting IASP members decrease their intramural R&D expenditure, thereby opening up to external collaborative R&D beyond their regional boundaries.

4.1 Robustness checks

We test the robustness of our findings through three sensitivity analyses, with results presented in Table 3 alongside our main estimates. First, we assess the sensitivity of our analysis to the choice of the number of lags (L). As discussed in Sect. 3.2, selecting L involves a bias-variance tradeoff with higher values improving robustness while reducing the number of potential matches. Given the size of our sample, we re-estimate the ATT for intermediaries and knowledge by selecting $L = 2$ (instead of $L = 3$ in our main specification). Second,

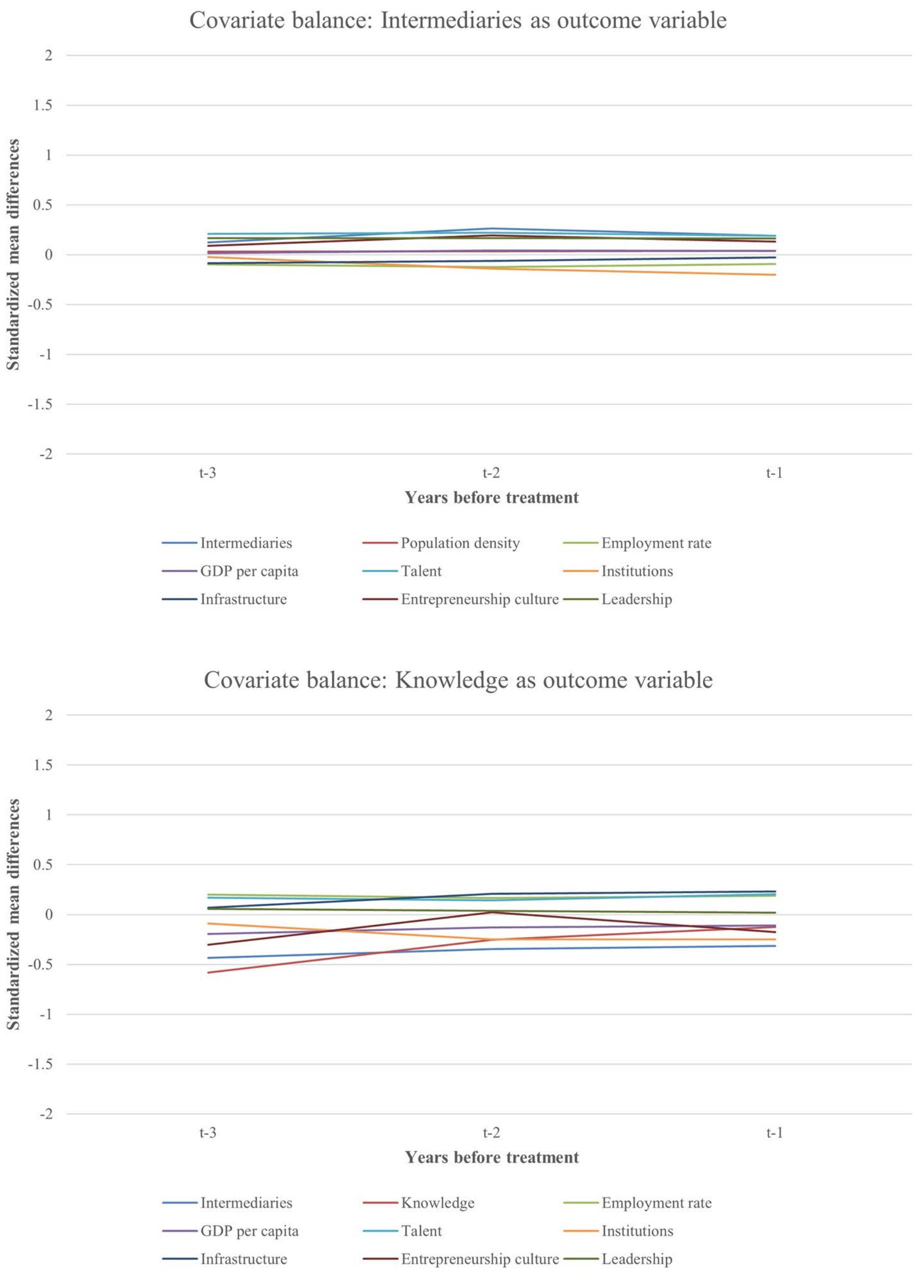
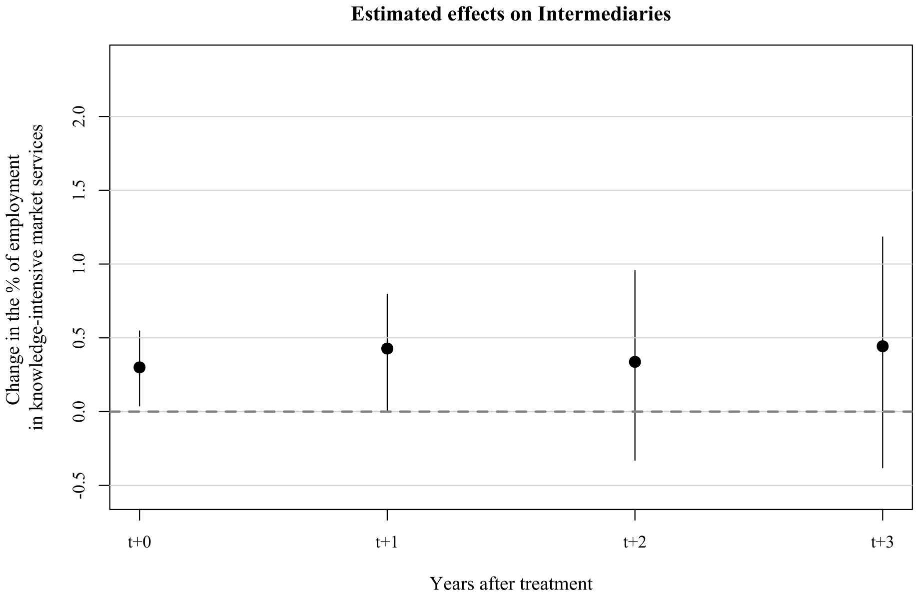


Fig. 2 Covariate balance between treated and control regions with intermediaries (top) and knowledge (bottom) as outcome variables



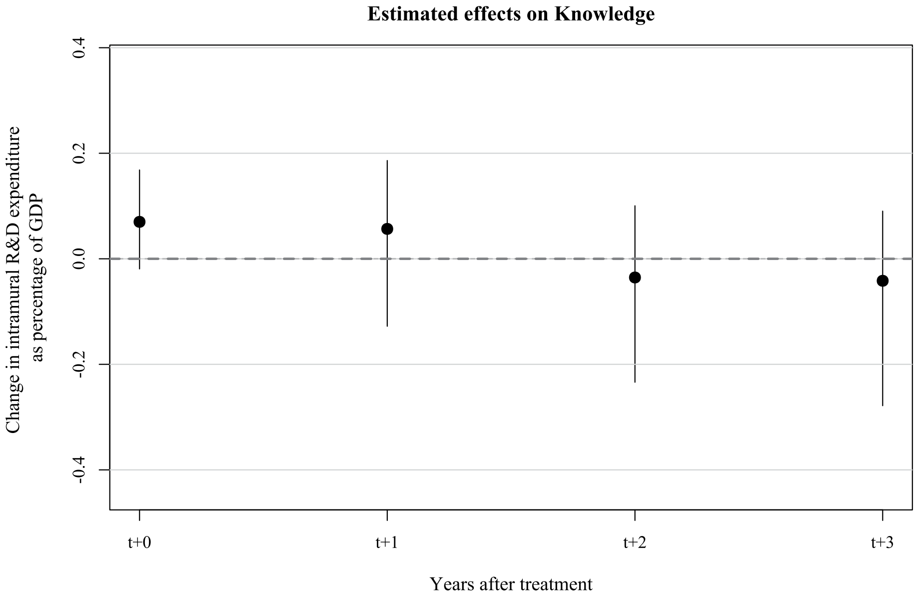


Fig. 3 Estimated average treatment effect among treated (ATT) on intermediaries and knowledge with 95% confidence levels

we vary the match set size, using 5 nearest neighbors rather than 3. Third, we employ a different matching method, replacing Mahalanobis distance with propensity score matching (PSM) (Rosenbaum & Rubin, 1983) to identify the set of control units for each treated region.

As for our main estimates, we first assess the covariate balance between treated and matched control units for each robustness check in Fig. 4. While varying the number of lags and match sizes returns balanced matches within the accepted standard deviation range $(-1, 1)$, our main specifications provide the most balanced matching, confirming the robustness of our approach. In contrast, PSM results in less efficient covariate balance than Mahalanobis distance, consistent with previous studies (Liberati et al., 2016; Zhao, 2004).

Table 3 shows that most robustness check estimates align with our main analysis. The effect of STPs' entry into IASP remains positive and statistically significant for the intermediaries dimension of regional EEs in the year of treatment and the following year. In particular, the estimated impact on employment in knowledge-intensive market services increases by approximately 0.4 at $t + 1$ and is statistically significant at the 5% level across all specifications (except for the PSM approach, which is less reliable due to covariate imbalance). The main difference concerns the year of treatment, where the estimated impact is lower and not statistically significant when using $L = 2$. When considering knowledge as the outcome variable, the effect consistently declines over time, becoming negative at $t + 2$, though it remains not statistically significant.

4.2 Heterogeneity tests

The effect of STPs' entry into IASP may also depend on the economic and geopolitical characteristics of the region. To explore potential heterogeneity in the impact of STP networks on regional EE development, we replicate our analysis – using the same set of parameters as in our main specification – while splitting regions based on GDP per capita and EU membership. Specifically, we conduct two heterogeneity tests. First, we divide regions into two groups based on the median GDP per capita among treated units in 2013 (the last common pre-treatment year for all treated regions). Second, we separate regions into EU and non-EU countries. The results are presented in Table 4.

Two key findings emerge from this analysis. Low-income regions experience an immediate increase in employment in knowledge-intensive market services (statistically significant

Table 3 Main estimates and robustness checks of the average treatment effect (ATT) on intermediaries and knowledge

	Intermediaries				Knowledge			
	t+0	t+1	t+2	t+3	t+0	t+1	t+2	t+3
Main estimates	0.300**	0.427**	0.337	0.443	0.070	0.057	−0.035	−0.042
	(0.133)	(0.196)	(0.324)	(0.383)	(0.048)	(0.077)	(0.088)	(0.102)
$L = 2$	0.196	0.402**	0.399	0.495	0.077	0.065	−0.041	−0.074
	(0.123)	(0.181)	(0.306)	(0.354)	(0.051)	(0.070)	(0.080)	(0.120)
Mahalanobis with 5 neighbors	0.245**	0.427**	0.420	0.553	0.069	0.056	−0.029	−0.040
	(0.110)	(0.179)	(0.293)	(0.337)	(0.052)	(0.068)	(0.077)	(0.099)
Propensity score matching	0.259**	0.289	0.267	0.332	0.049	0.39	−0.050	−0.081
	(0.107)	(0.205)	(0.331)	(0.402)	(0.055)	(0.075)	(0.090)	(0.130)

Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Standard errors are computed with 1000 weighted bootstrap samples

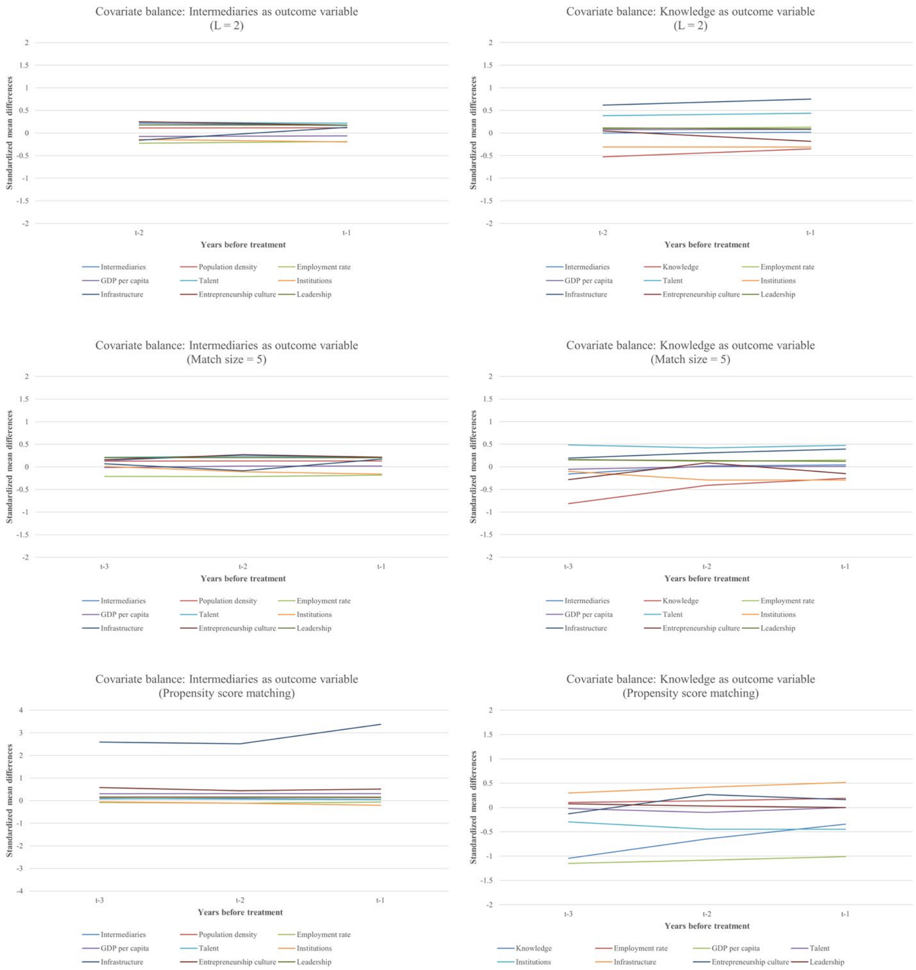


Fig. 4 Covariate balance: intermediaries and knowledge as outcome variables. Robustness checks using (i) $L = 2$, (ii) Mahalanobis distance with 5 neighbors, and (iii) propensity score matching

at the 10% level) in the year of treatment. This effect likely stems from increased visibility, which helps these regions attract skilled workers who would otherwise migrate to more economically developed areas. However, the effect does not persist over time; although the ATT loses significance, it turns negative in the second and third years after treatment. In contrast, high-income regions benefit more from STPs' entry into IASP starting in the first year after treatment, with a statistically significant effect at the 10% level, increasing employment in knowledge-intensive market services by 0.46 percentage points. In terms of intramural R&D investments, no particular heterogeneous effects are observed based on GDP per capita.

More pronounced heterogeneity emerges when differentiating between EU and non-EU regions. Extra-EU regions exhibit a statistically significant increase ($p < 0.05$) in knowledge-intensive employment – typically made of highly specialized workers – with a rise

Table 4 Heterogeneity effects

	Intermediaries				Knowledge			
	t+0	t+1	t+2	t+3	t+0	t+1	t+2	t+3
GDP per capita above median	0.194 (0.158)	0.461* (0.246)	0.473 (0.437)	0.627 (0.474)	0.033 (0.056)	0.123 (0.117)	−0.022 (0.117)	−0.047 (0.105)
GDP per capita below median	0.507* (0.274)	0.226 (0.395)	−0.247 (0.410)	−0.367 (0.613)	0.070 (0.059)	0.065 (0.088)	−0.032 (0.108)	0.005 (0.133)
EU member	0.111 (0.141)	0.197 (0.209)	0.122 (0.289)	0.214 (0.305)	0.060 (0.048)	0.081 (0.066)	−0.029 (0.079)	−0.010 (0.096)
Extra-EU	0.753** (0.345)	0.980** (0.419)	0.853 (0.895)	0.993 (1.105)	0.143** (0.071)	−0.117 (0.221)	−0.080 (0.221)	−0.267 (0.204)

Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Standard errors are computed with 1000 weighted bootstrap samples

of 0.75 and 0.98 percentage points in the year of treatment and the following year, respectively. This finding suggests that STP networks may act as complementary to EU policies in fostering cross-border knowledge transfers and resource sharing. Within the EU, such mechanisms are supported by the EU Research and Technological Development (RTD) policy, whereas STP networks appear to fulfill a similar role for extra-EU countries in the absence of such institutional frameworks. Finally, STPs' entry into IASP seems to stimulate R&D investments within extra-EU regions, significantly ($p < 0.05$) and positively affecting the knowledge dimension of the regional EE at the year of treatment. However, this effect reverses in the following years, becoming negative and not statistically significant.

5 Discussion and conclusion

In this paper, we examined the role of STP networks in shaping regional EE development. To this aim, we developed a multi-stage approach to assess the effects of STPs' entry dynamics into global networks on EE dimensions, focusing on the regions in which these parks are located. Specifically, we formulated two main research questions: (i) "Do STP networks affect regional EE development?" and (ii) "What EE dimensions are impacted by participation in STP networks, and when does the effect become observable?". We focused on IASP – the largest global STP network – benefiting from data on entry and exit dynamics of STPs from the network. This longitudinal dataset, which spans multiple European regions, allowed us to analyze whether participation in IASP leads to changes in EE dimensions, as defined by Stam (2015) and operationalized by Leendertse et al. (2022). To estimate these effects, we employed a non-parametric generalization of the DiD estimator for TSCS data, which is particularly suitable when the number of treated units is small and when pre-treatment periods are short (Imai et al., 2023). Our covariate balance analysis confirmed the comparability between treated and matched control units, supporting the validity and interpretability of our results, which were further reinforced by robustness checks.

Our findings addressed both questions, providing novel insights into the role of STP networks in regional EE development. Specifically, we found that STPs' entry into IASP led to a statistically significant increase in employment in knowledge-intensive market services within their regions in the year of treatment and the following year. This indicates that STP participation in global networks strengthens the intermediary services of regional EEs, extending previous studies that highlighted the role of other key intermediaries – such as incubators, accelerators, and universities – in facilitating resource distribution within ecosystems (Fuster et al., 2019; Pustovrh et al., 2020; Roundy, 2017). This finding reinforces a distinctive feature of STPs, which foster networking by strategically selecting tenants that are likely to interact and by directly brokering ties among them (Koçak & Can, 2014). In this sense, participation in global STP networks amplifies and extends the knowledge spillovers and positive externalities typically associated with STPs (Díez-Vial & Fernández-Olmos, 2015; Montoro-Sánchez et al., 2011), further confirming their capacity to stimulate higher job creation rates (Löfsten et al., 2020). At the same time, we observed a declining trend in intramural R&D expenditure from the year of treatment to the third year post-entry. Although not statistically significant due to the small number of treated units in this specification, this result aligns with the idea that joining an international network of STPs encourages collaborative R&D activities extending beyond regional boundaries. This pattern could suggest that within-ecosystem cooperation and knowledge-sharing practices are increasingly driven by other intermediaries, such as incubators and accelerators (Goswami et al., 2018; Pustovrh et al., 2020).

Our heterogeneity analysis highlighted the relevance of contextual factors (Stam & Van de Ven, 2021) and cross-country STP effects (Lopes et al., 2025) when assessing participation in global networks. Differences emerged between low- and high-income regions in terms of the timing of significant effects. Low-income regions experienced an immediate positive impact on intermediary services, potentially attracting skilled workers who might otherwise move toward more developed areas. In contrast, high-income regions showed delayed effects, becoming significant one year after entry. Heterogeneous effects were also observable between EU and extra-EU regions. Specifically, extra-EU regions exhibited a statistically significant increase in knowledge-intensive employment in the year of treatment and the following year, suggesting that STP networks may complement EU integration policies by fostering cross-border knowledge transfer and collaborative R&D. Furthermore, extra-EU regions also experienced a significant rise in intramural R&D investments in the year of treatment, highlighting the value of global STP affiliations for enhancing regional knowledge production. These results extend prior evidence on the role of STPs in boosting regional competitiveness and supporting the emergence of knowledge-based economies (Cumming et al., 2019; Theeranattapong et al., 2021).

This study offers several theoretical contributions. First, it responded to calls for longitudinal, comparative, and dynamic approaches to STP research (Albahari et al., 2023), complementing earlier studies that largely treated STPs as static entities (Lecluyse et al., 2019). By leveraging longitudinal data, we shed light on the mechanisms through which STPs operate, addressing one of the key barriers to advancing knowledge in this field (Audretsch & Belitski, 2019). Second, we emphasized the temporal evolution of STP network effects, showing their dynamic contribution to regional EE development. While prior research suggested that STP benefits materialize gradually (Díez-Vial & Montoro-Sánchez, 2016), our results revealed a sudden and significant increase in employment within knowledge-intensive market services already in the year of entry, which persists in the following year. Third, while prior studies demonstrated that on-park firms outperform off-park ones in terms of R&D efficiency (Yang et al., 2009; Siegel et al., 2003), we advanced the literature by shifting the focus to the macro-regional level. Specifically, our findings suggest that improved R&D efficiency may reflect a strategic reorientation of R&D activities toward international collaboration following entry into global STP networks. This is consistent with Minguillo et al. (2015), who observed that on-park firms often establish collaborations beyond their regional context. In this vein, STP networks serve as multipliers of previously observed micro-level benefits, such as talent attraction and innovation performance. Finally, we bridged STP and EE literatures, extending recent contributions (Germain et al., 2023; Kanda et al., 2025; Mohammadi et al., 2025), and answering recent calls for a deeper understanding of how global STP networks shape regional EE development (Hrebennyk et al., 2024).

Regarding practical implications, our results suggest that regional authorities should not only support the establishment of STPs but also promote their participation into global networks, as such affiliations generate positive spillovers for the entire region. These outcomes reinforce the IASP mission to foster international partnerships and demonstrate how STP networks can lower barriers to entry into global innovation systems (IASP, 2025). For STP managers, the findings shed light on the value of actively participating in international networks to strengthen their regional intermediary role and to access external knowledge flows. Moreover, STP networks may serve as effective policy instruments for talent attraction and cross-border collaboration, especially in regions lacking cohesive policy frameworks – such as those European countries outside the EU – providing an alternative mechanism for cross-border knowledge exchange and collaboration.

5.1 Limitations and future research

This study presents some limitations. First, despite broadening the scope of prior research, our sample size is constrained by the availability of data on EE dimensions and regional socio-economic indicators. However, this limitation was mitigated by employing a non-parametric DiD estimator suited to small-sample settings (Imai et al., 2023). Second, certain effects of STP networks may become more evident when analyzed at a finer spatial scale (e.g., at the NUTS-3 level), highlighting the need for greater data granularity – an aspect that would be valuable to collect and integrate in future analyses (Hess et al., 2025). Third, while we estimates the effects induced by STP network participation as average treatment effects, such benefits likely vary with parks' absorptive capacity and engagement levels. In this context, governance failures and coordination frictions among network members may further attenuate these benefits. While international collaboration can foster employment in knowledge-intensive market services, it simultaneously increases decision-making complexity and the risk of misaligned incentives and uneven commitment among local stakeholders. Future research should investigate this heterogeneity through in-depth, multiple case studies, delving into the diversity within and across STPs in terms of member size, absorptive capacity, and relational capabilities – both among network members and in their interactions with external institutional and governmental actors. Fourth, our findings are based on the analysis of IASP, the largest and most influential global association of STPs. Therefore, the observed positive effects may, in part, reflect IASP's central position within the global STP landscape and may not fully extend to smaller or less integrated networks. Comparative studies involving other STP networks are thus essential to assess the generalizability of our results. Finally, we acknowledge that long-term participation in global STP networks may generate lock-in effects, as repeated collaboration patterns and standardized governance models can lead to institutional rigidity and reduced adaptive capacity for both tenant firms and STPs as a whole. These conditions may constrain the potential for the development of regional EEs, suggesting that the positive effects observed are more likely to occur under dynamic and open governance configurations. In this vein, future research could incorporate social network analysis techniques to map the evolution of global connectivity among STPs and assess their relational structures through centrality measures and network metrics. This approach would help identify when and how STP network structures transition from open and adaptive configurations to more rigid, path-dependent forms, thereby clarifying how eventual lock-in effects and emerging structural boundaries may hinder the benefits generated through network participation.

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Author contributions Andrea Ancona and Giuseppe Ceci contributed to conceptualizing, writing, and reviewing the manuscript. Andrea Ancona and Giuseppe Ceci contributed to data collection and cleaning. Andrea Ancona conducted the statistical analysis. Giuseppe Ceci conducted the expert interview.

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Data availability The complete list of regions—including the number of STPs and the years of treatment—is provided in Online Appendix A. The authors do not have the permission to disclose data at the STP level.

Declarations

Conflict of interest The authors declare no conflict of interest.

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