Medium-term regional effect of Science and Technology Parks: a staggered difference-in-difference approach

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Abstract

The interest in regional innovation policies has increased in recent years. Science and Technology Parks (STPs) are one of the most widespread regional innovation policies worldwide. They are considered a catalyst for regional innovation because they constitute a source of knowledge spillovers and a mechanism for knowledge transfer. The aim of this work is to evaluate the effect of the adoption of the STP policy on regional innovation performance. To this end, we build a provincial dataset for Spain covering 37 years and implement a difference-in-differences approach taking advantage of the staggered adoption of the STP policy and the fact that some provinces do not have an STP yet. The main results show that STPs increase provincial patents by 49.8% in years 6-10 after the adoption of the policy and by 79.7% in years 11-15.This result is robust to different assumptions and methodological choices. In addition, we find that the increase in patents does not come at the cost of lower patent quality, that STPs perform similarly in more or less advanced provinces, and that approximately 57% of the effect comes through STP spillovers.

Keywords: Science and Technology Parks; innovation policy evaluation; regional effects; spillovers; patents; diff-in-diff

1. Introduction

Regional innovation policies have emerged as one of the priorities for many governments (Uyarra et al., 2017), so that there is a need to evaluate these policies and, especially, the role played by agglomerations in the relationship between innovation policies and the performance of regions (Samara et al., 2012). Among these policies, Science and Technology Parks (STPs) are one of the more widespread in both developed and developing countries (Hobbs et al., 2017; Rodríguez-Pose and Hardy, 2014; Rowe, 2014).

STPs are property-based initiatives, designed to encourage the creation and growth of on-site technology- and knowledge-based firms, with a management function actively engaged in achieving these goals. They have been mostly the result of political decisions, involving considerable public investment (Albahari et al., 2013) and representing one of the main regional innovation policy initiatives (Vásquez-Urriago et al., 2016a). So far, the vast majority of studies on STPs have focused on the impacts of on-park location for companies by comparing the performance of similar firms located on and off-park. The empirical evidence is mixed (Albahari et al., 2023; Hobbs et al., 2017; Lecluyse et al., 2019). As instruments of public policy, STPs are designed to foster innovation and growth not only of their tenant organizations, but also to stimulate the broader regional economy (Felsenstein, 1994; Vásquez-Urriago et al., 2014). The importance of adopting a regional perspective when evaluating geographically bounded policies is increasingly supported by the literature (see, for instance Gkypali et al., 2016; Lecluyse et al., 2019; Nauwelaers et al., 2019), in order to fully understand their effectiveness and scope. Nonetheless, very few studies adopt a regional perspective when assessing the impacts of STPs (Albahari et al, 2023).

The main goal of this paper is to analyse the effect that STPs on the innovation performance of the provinces where they are established

To this end, we build a database of Spanish provincial data between 1980 and 2016 and apply a staggered differences-in-differences approach, taking advantage of the fact that not all provinces have adopted the STP policy as well as that the adoption took place over two decades.

We estimate the STP effect on provincial patents, which is found to be increasing in time. More precisely, in years 6-10 after the adoption of the policy, the STP effect is around 49.8%, while in years 11-15 it grows to approximately 79.7%. We test the robustness of this main result to different assumptions and methodological choices. We also show that: i) the additional patents generated are of similar quality, ii) the STP effect is not explained by provincial characteristics and iii) around 57% of the effect comes through STP spillovers on off-Park firms.

The remainder of this paper is organised as follows: section 2 reviews the literature on STPs and their regional effect; section 3 explains data and empirical strategy; section 4 presents the main results and the robustness checks; section 5 presents results from further analysis; and section 6 concludes.

2. Literature review

STPs are considered as innovation and economic regional catalysts or revitalizers due to their influence on creating an environment where new-established firms may thrive, fostering university-industry links, and upgrading the entrepreneurial activities within the region (Gkypali et al., 2016; Gomes et al., 2022). In this way, STPs are expected to contribute to the development of their regions (Link and Scott, 2006), in which they may play a key role in the local innovation ecosystem (Albahari et al., 2019). We can distinguish two main ways through which STPs influence regional innovation performance: their effects on tenants and their effects on non-STP organizations.

Research focusing on the impact of STPs on their tenants is flourishing (Albahari et al., 2023) and generally explores three key dimensions: economic performance, innovation outcomes, and patterns of cooperation, particularly with universities and research centres.

First, studies evaluating the impacts of STPs on the economic performance of tenants, commonly use indicators such as employment growth (Colombo and Delmastro, 2002), sales growth (Diez-Vial and Fernández-Olmos, 2017), productivity (Hasan et al., 2020), and profitability (Liberati et al., 2016). Second, other research focuses on the effects of STPs on innovation, examining inputs of the innovation process, such as R&D intensitiy (Lamperti et al., 2017) and workforce quality (Martín-de Castro et al., 2023), as well as outputs like patenting activity (Corrocher et al., 2019), patent quality (Anton-Tejon et al., 2024) and new product development and sales (Vásquez-Urriago et al., 2016a). Across both economic and innovation dimensions, the literature leads to non-conclusive results, with some studies finding positive effects of STPs, while others do not find significant evidence.

Finally, the literature reveals that the proximity provided by STPs is believed to enhance interaction and cooperation between tenant firms and external entities. In this case, most papers find a greater propensity for on-park firms to engage in collaborations (Vásquez-Urriago et al., 2016b), including off-park firms and universities (Colombo and Delmastro, 2002; Díez-Vial and Fernández-Olmos, 2015; Felsenstein, 1994).

This evidence on STPs facilitating interaction and cooperation among on-park firms and external entities, supports the view of STPs as a regional innovation policy with effects beyond their immediate boundaries. STPs bring together some theoretical arguments that suggest positive effects also outside their perimeters, particularly in their surrounding regions.

First, STPs could foster Marshallian externalities in neighboring regions (Helmers, 2019). These refer to the existence of economies of specialisation, labour market economies and knowledge spillovers (Breschi and Lissoni, 2001). The hosting of multiple firms within the same or related sectors by the park encourages the emergence of specialised suppliers and service providers in the region, which not only benefits the tenants of the park, but also extends advantages to companies outside the park, which can access to specialised inputs crucial for their operations more easily and at a lower cost. STPs attract a skilled workforce with specialized expertise in specific regions (Cadorin et al., 2021). This generates a pooling of labour in the region that benefit companies in the park's region.

Second, The STP ecosystem facilitates the triple-helix-based interactions among tenant firms and other regional agents, including research institutions, universities, and policymakers (Etzkowitz and Zhou, 2018), making new innovations thrive (Phillimore, 1999). Particularly, the university aplays a fundamental role for STPs in providing a pool of high-skilled workforce (Vedovello, 1997), boosting academic entrepreneurship (Löfsten et al., 2020) and knowledge transfer (Autio et al., 2018). In turn, STPs become a suitable environment for entrepreneurial activities, given their services and facilities for the development of business projects (Albahari et al., 2018). In addition, the importance of public institutions in STPs is not negligible since these are dependent on public infrastructures such as transportation, housing, schools, and medical facilities built by public institutions (Etzkowitz and Zhou, 2018). Furthermore, public institutions may influence the management of STPs and provide financial resources for the development of these ecosystems (Biswas, 2004).

Third, the different types of proximity (Knoben and Oerlemans, 2006) fostered by STPs that are indicated as one of the sources of the added value of on-park location (Albahari, 2021) can be generated not only intra-park, but also in the vicinity of the park itself. The physical closeness of STPs to local businesses and academic institutions can facilitate face-to-face interactions, which are crucial for the exchange of tacit knowledge (Gertler, 2003). This proximity can enhance collaborative R&D projects between tenants of the park and geographically close external stakeholders, leading to innovations that benefit the broader region. STPs often act as hubs for networking events, workshops, conferences, etc. (Harper and Georghiou, 2005) that bring together a diverse group of stakeholders, including entrepreneurs, researchers, investors, and policymakers. These interactions among actors belonging to different organisations in the region, can foster strong social networks that facilitate the flow of knowledge across the regional innovation ecosystem.

Despite these arguments, the extant literature on STPs have paid little attention to the regional effects of STPs (Poonjan and Tanner, 2020). In particular, the few authors that have attempted to assess the effects of STPs on their regions, have focused on economic growth, measured using employment, creation of new ventures or Foreign Direct Investment (FDI), with contrasting results.

Luger and Goldstein (1991) found that US counties with university-affiliated STPs experienced greater total employment growth. Jenkins et al. (2008), analysing the change in US metropolitan areas, found that STPs have direct effects on the the share of high-technology employment. Similarly, Hu (2008) and Vaidyanathan (2008) show that the establishment of STPs leads to fostering the economic growth of regions through the rise of Foreign Direct Investments (FDI), primarily because of their attractiveness for large multinational companies. Conversely, these positive results are refuted by Shearmur and Doloreux (2000), who find that the Canadian STPs did not stimulate high-tech employment, as well as Ratinho and Henriques (2010) and Storey and Tether (1998) argue that the contribution of STPs to economic growth and employment is modest.

From an innovation point of view, although there is a large body of empirical evidence on STPs effects on tenants' innovation performance, innovation studies adopting a regional perspective of STPs are almost entirely missing. The only notable exception, as far as we know, is a recent paper by Gomes et al. (2022), who study the Portugal case through a qualitative approach, suggesting that STPs enhance various indicators of the innovation activity and performance, of the regions where they are established.

This very limited evidence on the effects of STPs at the regional level prompted Lecluyse et al. (2019) to call for further research on how STPs and regions interact and how they contribute to regional development.

3. Data and empirical strategy

3.1. Spanish STPs

In our analysis, we use Spanish provincial data. Spain is made up of 50 provinces and 35 of them have adopted the STP policy, while 15 provinces remain without an STP in 2024. According to the data published annually by the Spanish Association of Science and Technology Parks (APTE) on its website, there are currently over 50 operational parks, which house 5,780 companies, employing 150,624 workers, of which 34,190 are dedicated to Research and Development (R&D) activities. The turnover of all the companies in the park amounts to 25,148 million Euros (APTE, 2023). The adoption of the STP policy has been staggered, as it is illustrated in Figure 1.

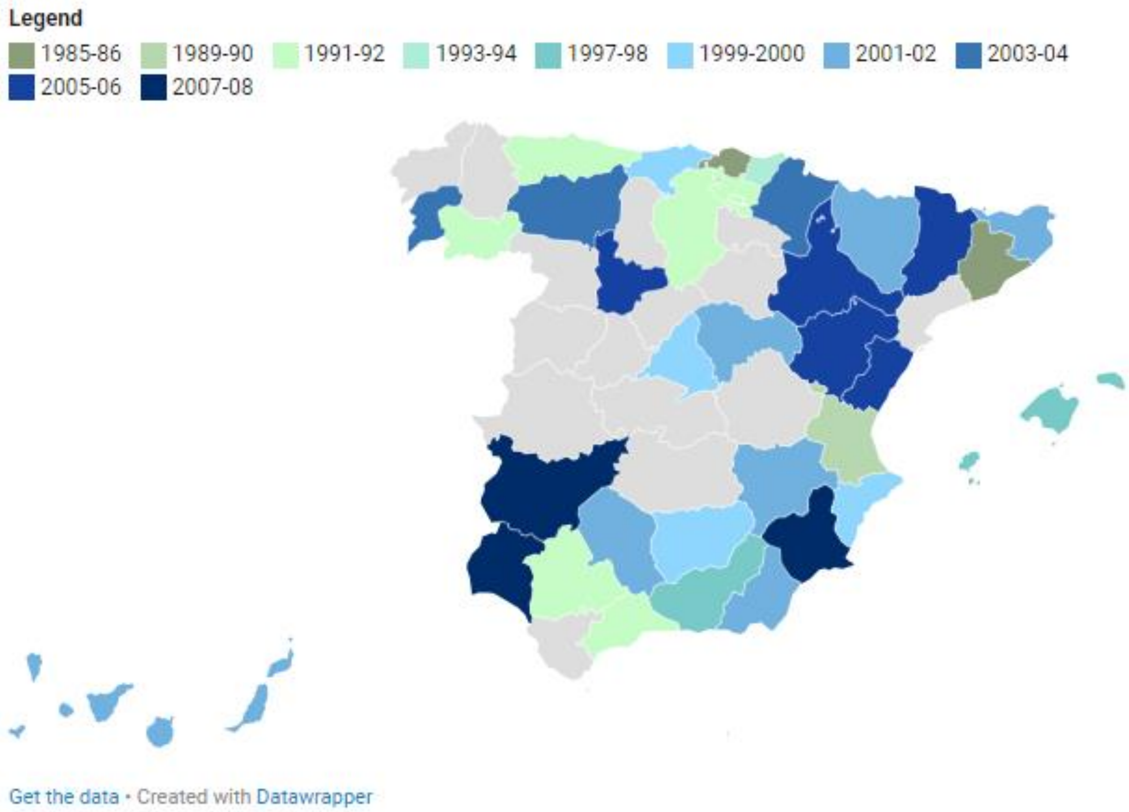


Figure 1. Provinces with an STP by date of establishment

3.2. Dataset

We build a provincial panel dataset between 1980 and 2016 (1,850 observations) combining three different sources of information.

First, we use the June 2023 version of the REGPAT database from the OECD (Organisation for Economic Co-operation and Development). The information contained in REGPAT, including the full addresses of applicants and inventors of patents, allows us to geographically locate the patents at the NUTS 3 level (Maraut et al., 2008). REGPAT contains information on patent applications from the EPO (European Patent Office) and Euro-PCT (Patent Cooperation Treaty). Both types of patent applications differ in their process, rights, and laws. The first via is only subjected to the European

Patent Convention (EPC), whereas patent applications to the Euro-PCT undergo two phases, PCT in the first phase and EPC in the second phase.[1]

Second, province economic data has been drawn from different surveys administered by the *National Statistic Institute* (INE). For our study, we have drawn data from *Spanish Regional Accounts* (CRE) – GDP per capita, *Continuous Statistic of Population* (ECP) – Population data, *Working-age Population* (EPA) – Unemployment data, and Working-age population.

Third, the annual APTE (Association of Science and Technology Parks of Spain) directories, which allow us to know the year of creation and the provinces of every STP.

3.3. Empirical strategy

Our study intends to estimate the effect of STPs on the innovation performance of the provinces where they are established. To this end, we compare the evolution of the performance of the provinces adopting the STP policy with the evolution of the performance of the provinces not adopting the STP policy. That is, we rely on a difference in differences methodology. The key identification assumptions for this comparison to provide causal effects are parallel trends (the innovation performance for provinces with and without STPs would have evolved in parallel if the STP policy has not been adopted) and no anticipation (innovation performance before the adoption of the STP policy is not affected by the upcoming STP policy).

Differences in differences have been an increasingly important empirical method to analyse causal effects, being used by around 25% of NBER Working Papers in applied micro between 2015 and 2019 (Currie et al., 2020), with this percentage being even a bit higher between 2020 and 2024 (Goldsmith-Pinkham, 2024). The more common strategy to apply differences in differences has traditionally been a regression with time and groups fixed effects (TWFE), accounting for 26 of the 100 most cited papers in the American

[1] There is a delay between the date of application and the dataset. This is due to several reasons such as applicant decisions on patent scope, delays in patent offices, and updates of databases. With the purpose of having consistent patent data, the last period considered is 2016.

Economic Review between 2015 and 2019 (Chaisemartin and D'Haultfoeuille, 2022). However, it has been shown that TWFE does not work well under staggered interventions if there is heterogeneity in treatment effects across either time or units. The reason for this is that TWFE uses 'forbidden comparisons' in which early-treated units serve as the control group for those units treated later, which gives place to negative weights for some treated units so that the resulting estimate does not identify any meaningful causal effect (Chaisemartin and D'Haultfoeuille, 2022; Goodman-Bacon, 2021).

In our setting, we deal with a staggered intervention and the treatment effects are expected to greatly vary with time (as the STP effect on regional performance is expected to be revealed after several periods). Fortunately, some proposals have been made in the literature to deal with staggered interventions (Borusyak et al., 2023; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Wooldridge, 2021). Arguably, the most popular method has been the one proposed by Callaway and Sant'Anna (C&S henceforth).

Intuitively, C&S identifies the average treatment effect on the treated for each cohort g and for each period t, which is denoted by ATT(g,t), by comparing the expected change in outcome for cohort g between periods g-1 and t to the expected change in outcome for a control group either never treated or not-yet treated at period t (which, under the assumptions, is an adequate counterfactual to ascertain what would have ocurred to the treated provinces had they not been treated).[2]

$$ATT(g,t) = E\left[Y_{it} - Y_{ig-1} | G_i = g\right] - E\left[Y_{it} - Y_{ig-1} | G_i = \cancel{g}\right] \qquad (1)$$

In Equation 1, g-1 is the year before cohort g enters into treatment and $\cancel{g}$ is the control group that, in our setting, can be those provinces never treated or those provinces not yet treated. $\widehat{ATT}(g,t)$ is estimated by replacing expectations with sample analogues.

That is, C&S performs many 2x2 comparisons. When there is a relatively small number of periods and treatment cohorts, reporting all the relevant $\widehat{ATT}(g,t)$ can be reasonable.

[2] This formula identifies the ATT under the staggered version of the parallel trends and no anticipation assumptions.

However, when there are many treated periods and/or cohorts, reporting all the $\widehat{ATT}(g,t)$ may be cumbersome and, in addition, each of them is estimated with low precision. To deal with this issue, C&S proposes ways to aggregate the effects by cohort or time since treatment. This approach shows two main advantages over TWFE: it provides sensible estimands even under arbitrary heterogeneity of treatment effects and it makes transparent exactly which units are being used as a control group to infer the unobserved potential outcomes (Roth et al., 2023).

3.4. Dependent variable: patents

We proxy innovation performance by using the number of patent applications per capita as dependent variable.[3] More precisely, we define the patent indicator as follows:

$$Patent\_PC_{i,t} = \frac{EPO_{i,t} + PCT_{i,t}}{Population_{i,t}} \ x\ 1{,}000{,}000$$

where $Patent\_PC_{i,t}$ are patent applications per million inhabitants in the province i and year t. $EPO_{i,t}$ is the number of EPO applications, $PCT_{i,t}$ is the number of PCT applications[4], and, finally, $Population_{i,t}$ is the number of inhabitants (in millions) in the province i and year t.

Patents have usually been considered an appropriate indicator of innovation at the regional level. Despite the fact that not all innovations are patented (Arundel and Kabla, 1998), it has been shown that there is a strong relationship between innovations and patents at the regional level (Acs et al., 2002; Lee et al., 2004), leading to the extensive use of patents as an indicator for regional innovation performance (Crescenzi and Rodríguez-Pose, 2013; Fritsch and Slavtchev, 2011; Moreno et al., 2005). Table A1 in Appendix 1 reports descriptive statistics of our variables.

4. Results

[3] This indicator has been widely used in previous studies (see e.g., Crescenzi and Rodríguez-Pose, 2013; Fu, 2007; Lee et al., 2004). As an alternative indicator, we use the log of patents. Results (available upon request) are similar to the ones presented here.

[4] REGPAT database contains EPO and PCT patents. We thoroughly examine whether patents are not doubled-counted by identifying those PCT patents that have entered the EPO process. These PCT patents are considered as EPO patents vía PCT and are only counted as EPO patents.

4.1. Baseline Results

Column 1 in Table 1 shows the average treatment effects (across time periods and cohorts) estimates for the first 15 years after the adoption of the STP policy. In the first row, the never treated (*NT*) provinces are used as the control group; while in the second row the not-yet-treated (*NYT*) provinces are used as the control group. The results show that, on average, provinces adopting the STP policy show between 6.9 and 7.7 patents more per 1 million inhabitants every year, and the effect is statistically significant. In relative terms, this effect corresponds to an increase of around 46.82% in patents.[5]

However, this average result does not allow us to observe the dynamics of the STP effect. Figure 3 shows the effects aggregated according to the year to/after the establishment of the STP. We observe several interesting features in this 'event study' graph.

First, the number of patent applications in the treated- and non-treated-provinces is very similar in the 5 years previous to the creation of the STP, which suggests the compliance of the parallel trends assumption. Second, after the creation of the STP, we observed that the patent per capita from treated provinces increased slightly faster than those from non-treated provinces. However, the difference is not statistically significant during the first 5 years. Third, the differences become statistically significant from the sixth year after the STP creation. Fourth, the magnitude of the effect is quite large and, more importantly, increases over time..

4.2. Robustness check: introducing covariates

Despite Figure 3 supporting the parallel trends assumption, we want to obtain an extra-degree of robustness on this issue by imposing only parallel trends conditional on some covariates (Roth et al., 2023).

[5] This percentage has been calculated using the following procedure. Fitted values of Patent_PC are calculated for each province in the observed and the counterfactual situations using the simple C&S and the NT as the control group. We compute the average patents in the two situations, and the result is that the average patents for provinces with an STP are 46.82% larger than the average patents for the counterfactual situation in which these provinces do not adopt the STP policy.

It could be argued that those provinces with better economic conditions before the adoption of the policy follow a different patenting trend than those provinces with worse economic conditions. To control for this issue, we use two variables: Gross Domestic Product per capita (*GDPpc*) in thousands of Euros per person and Unemployment Rate (*unem*).[6]

C&S provides several ways to non-parametrically identify the group-time ATTs using pre-treatment covariates, relying on (i) modelling the conditional expectation function using the regression adjustment procedure (Heckman, 1998; Heckman et al., 1997), (ii) modelling the propensity score, that is, the conditional probability of being treated according to the covariates (Abadie, 2005) or (iii) using a 'doubly-robust' estimator that is valid if either the outcome model or the propensity score model is correctly specified (Sant'Anna and Zhao, 2020). The estimated effects using these three approaches are shown in Columns 2, 3 and 4 of Table 1.

We can see that the results with covariates are very similar to the results without covariates, suggesting that the counterfactual trends of treated provinces can be adequately represented using the untreated provinces. The similar results when using never-treated or not-yet-treated provinces also reinforces this view.

[6] The availability of indicators dating back to 1980 (to cover at least 5 years before treatment for every treated province) is very limited. Nevertheless, both GDPpc and unemployment rate have been shown to be indicators related to economic development and innovation (Crescenzi and Rodríguez-Pose, 2013; Ganau and Grandinetti, 2021).

Table 1. STP effect on regional innovation performance

	Simple C&S	REG estimator	IPW estimator	DRIPW estimator
	(1)	(2)	(3)	(4)
	Patent_PC	Patent_PC	Patent_PC	Patent_PC
Park (NT)	7.441***[2.474]	7.579***[2.941]	7.040**[3.510]	7.757**[3.263]
Park (NYT)	7.038***[2.503]	7.516***[2.821]	6.961**[3.293]	7.517**[3.175]
Control variables	NO	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
N	1848	1848	1848	1848

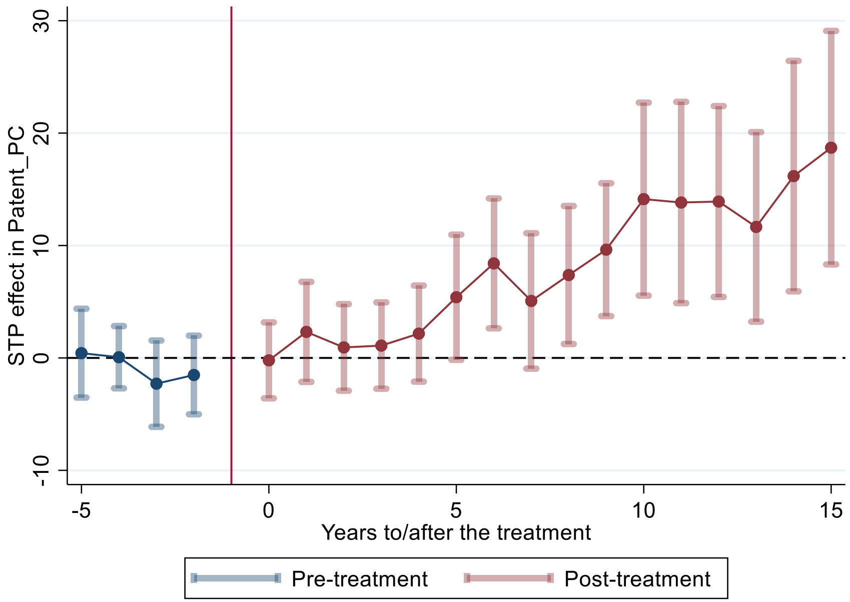
Notes: The dependent variable Patent_PC is patent per 1 million inhabitants. Control variables: *GDPpc* and *unem*. NT stands for never treated. NYT stands for not yet treated. The effects are computed for the first 15 years after the adoption of the STP policy. * p < 0.10, ** p<0.05, ***p<0.01.
Column (1) shows the results for C&S without covariates. Column (2) shows the results for regression adjustment (REG) procedure estimator. Column (3) shows the results using Inverse Probability Weighting (IPW) to model the propensity score . Column (4) shows the results for doubly robust (DRIPW) estimator.

4.3. Robustness check on the dynamics of the effect

For provinces adopting the STP policy after 2002, we are not able to observe the effects for the whole period of 15 years. For this reason, the long-term effects in the event study are computed using only the provinces that adopted the STP policy before 2003, while the short-term and medium-term effects are computed using also the provinces that adopted the STP policy later than 2003. For example, consider a province adopting the STP policy in 2006. We observe the patents for this province only for 11 years after the adoption of the STP policy which means that this province is included for years t to t+11, but not for years t+12 to t+15. As a consequence, what looks like a dynamic effect could be the consequence of heterogeneous effects across cohorts, with the effect being larger for the provinces adopting the STP policy earlier. To analyze if this is the case, we have carried out an additional analysis including only the provinces treated with an STP that can be observed for at least 15 years after treatment (we call it ‘subsample 15 years’ in the tables and figures). Table 2 shows the aggregated ATTs, which are statistically similar to those in Table 1. Figure 4 shows the event-study graphs, where we can appreciate that the dynamic pattern revealed by Figure 3 is still there, showing the the dynamic effect of STPs is not due to heterogeneous effects across cohorts but to the intrinsic dynamics of the effect. If we compute the magnitude of the effects by lustrum, in years 6-10 after the adoption of the policy the STP effect is around 49.76% and in years 11-15, it grows up to approximately 79.73%.[7]

[7] This percentage has been calculated using the following procedure. Fitted values of Patent_PCper are calculated for each province in the observed and the counterfactual situations using the simple C&S and the NT as the control group. We compute the average patents in the two situations, and compare them by lustrum.

Control group: Never Treated



Control group: Not Yet Treated

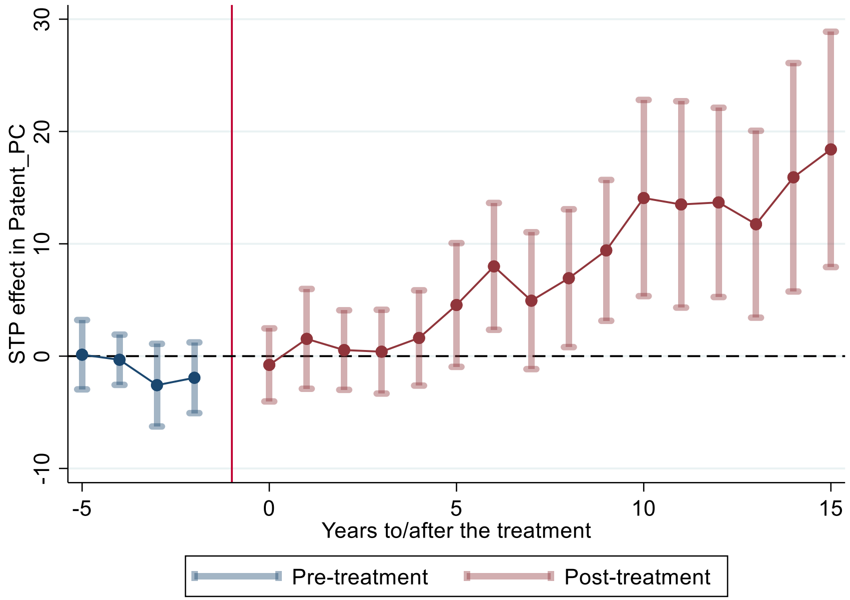


Figure 3. STP effect on patents per cápita. Event Study Graphs

Patent_PC as innovation indicator. Callaway and Sant'Anna (2021) method for DID models with panel data, using simple C&S estimator, implemented using csdid in Stata with the option long2 (using long differences for pre-treatment periods). Event time point estimates and 95% confidence intervals plotted. ATT stands for average treatment effect on the treated.

Table 2. STP effect on regional innovation performance (subsample 15 years)

	Simple C&S	REG estimator	IPW estimator	DRIPW estimator
	(1)	(2)	(3)	(4)
	Patent_PC	Patent_PC	Patent_PC	Patent_PC
Park (NT)	8.174***[2.976]	8.290**[3.761]	7.998*[4.457]	8.798**[4.137]
Park (NYT)	7.938*** [2.929]	8.357** [3.713]	8.174* [4.299]	8.805** [4.103]
Control variables	NO	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
N	1480	1480	1480	1480

Notes: The dependent variable Patent_PC is patent per 1 million inhabitants. Control variables: *GDPpc* and *unem*. NT stands for never treated. NYT stands for not yet treated. The effects are computed for the first 15 years after the adoption of the STP policy and only the treated provinces observed at least for 15 years after the adoption of the STP policy are included. * $p < 0.10$, ** $p<0.05$, ***$p<0.01$.

Column (1) shows the results for C&S without covariates. Column (2) shows the results for regression adjustment (REG) procedure estimator. Column (3) shows the results using Inverse Probability Weighting (IPW) to model the propensity score . Column (4) shows the results for doubly robust (DRIPW) estimator.

4.4. Robustness check: Madrid and Barcelona

An additional matter of concern is that two provinces that adopted the STP policy, Barcelona and Madrid (in 1985 and 2000, respectively) are by far the largest provinces in Spain, accounting together for around 50% of patent applications in the period of our sample, so that the results could be driven by their patenting activity.

Table 3 shows the results of removing Madrid and Barcelona from the sample. The STP effect remains positive and statistically significant, although it decreases slightly (still well inside the 95% confidence intervals of the main specification). Figure 5 shows the corresponding event studies, which are very similar to those from the main specification. All in all, this robustness check shows that the STP effect is not driven by the fact that the largest provinces (Madrid and Barcelona) have adopted the STP policy.

Control group: Never Treated. *Control group: Not Yet Treated*

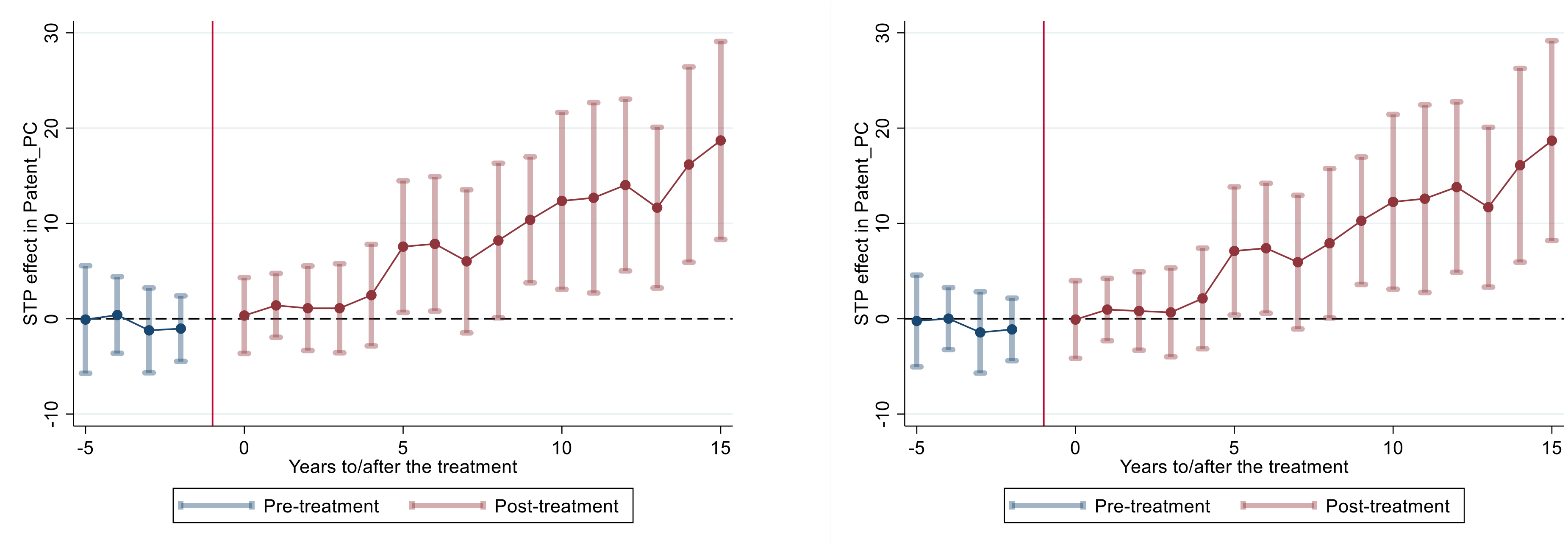


Figure 4. STP effect on patent intensity. Event study graphs excluding treated provinces with less than 15 years of treatment. Patent_PC as innovation indicator. Callaway and Sant'Anna (2021) method for DID models with panel data, using simple C&S estimator, implemented using csdid in Stata with the option long2 (using long differences for pre-treatment periods). Event time point estimates and 95% confidence intervals plotted. ATT stands for average treatment effect on the treated.

Table 3. STP effect on regional innovation performance (without Madrid and Barcelona)

	Simple C&S	REG estimator	IPW estimator	DRIPW estimator
	(1)	(2)	(3)	(4)
	Patent_PC	Patent_PC	Patent_PC	Patent_PC
Park (NT)	6.206*** [2.393]	6.117** [2.521]	5.828** [2.592]	5.945** [2.474]
Park (NYT)	5.860** [2.440]	6.117** [2.459]	5.658** [2.406]	5.723** [2.375]
Control variables	NO	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
N	1774	1774	1774	1774

Notes: The dependent variable Patent_PC is patent per 1 million inhabitants. Control variables: *GDPpc* and *unem*. NT stands for never treated. NYT stands for not yet treated. The effects are computed for the first 15 years after the adoption of the STP policy and Madrid and Barcelona are not included. * p < 0.10, ** p<0.05, ***p<0.01.

Column (1) shows the results for C&S without covariates. Column (2) shows the results for regression adjustment (REG) procedure estimator. Column (3) shows the results using Inverse Probability Weighting (IPW) to model the propensity score . Column (4) shows the results for doubly robust (DRIPW) estimator.

Table 4. STP effect on regional innovation performance (without Madrid and Barcelona, subsample 15 years)

	Simple C&S	REG estimator	IPW estimator	DRIPW estimator
	(1)	(2)	(3)	(4)
	Patent_PC	Patent_PC	Patent_PC	Patent_PC
Park (NT)	6.645** [2.905]	6.465** [3.229]	6.569** [3.233]	6.550** [3.149]
Park (NYT)	6.486** [2.872]	6.621** [3.174]	6.693** [3.168]	6.583** [3.113]
Control variables	NO	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
N	1406	1406	1406	1406

Notes: The dependent variable Patent_PC is patent per 1 million inhabitants. Control variables: *GDPpc* and *unem*. NT stands for never treated. NYT stands for not yet treated. The effects are computed for the first 15 years after the adoption of the STP policy, Madrid and Barcelona are not included and only the treated provinces observed at least for 15 years after the adoption of the STP policy are included. * p < 0.10, ** p<0.05, ***p<0.01.

Column (1) shows the results for C&S without covariates. Column (2) shows the results for regression adjustment (REG) procedure estimator. Column (3) shows the results using Inverse Probability Weighting (IPW) to model the propensity score . Column (4) shows the results for doubly robust (DRIPW) estimator.

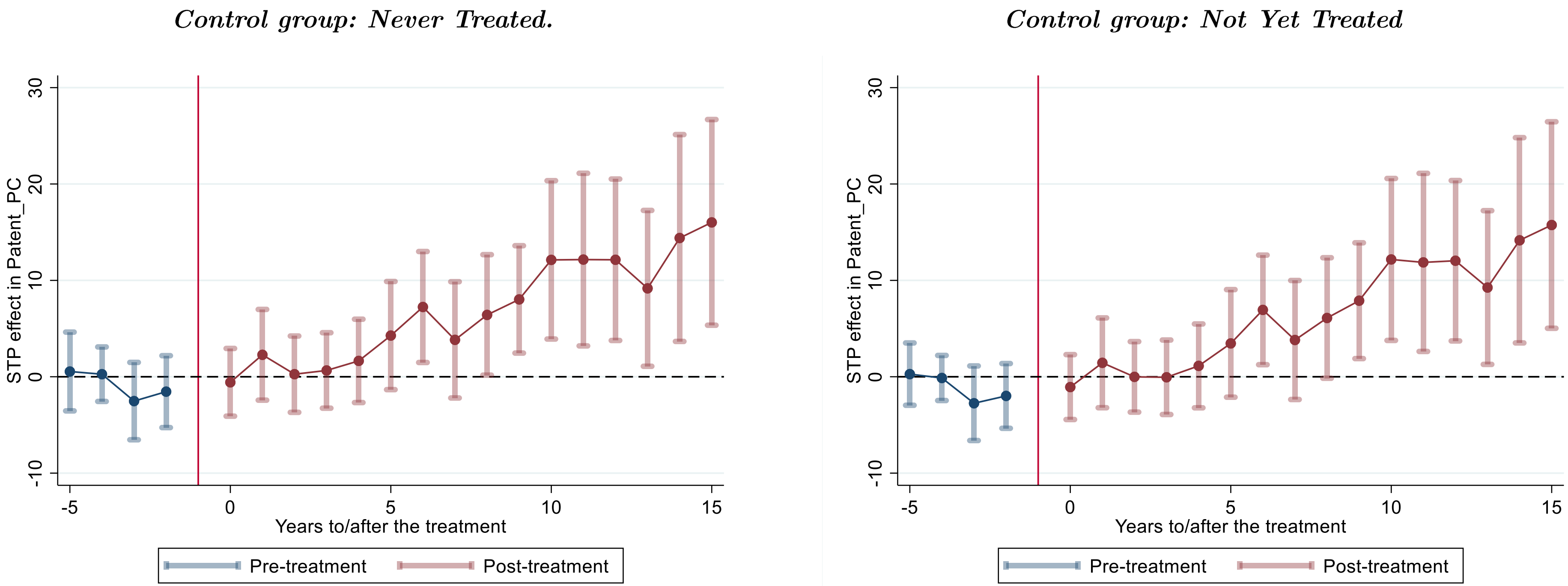


Figure 5. STP effect on patent intensity. Event study graphs without Madrid and Barcelona

Patent_PC as innovation indicator. Callaway and Sant'Anna (2021) method for DID models with panel data, using simple C&S estimator, implemented using csdid in Stata with the option long2 (using long differences for pre-treatment periods). Event time point estimates and 95% confidence intervals plotted. ATT stands for average treatment effect on the treated.

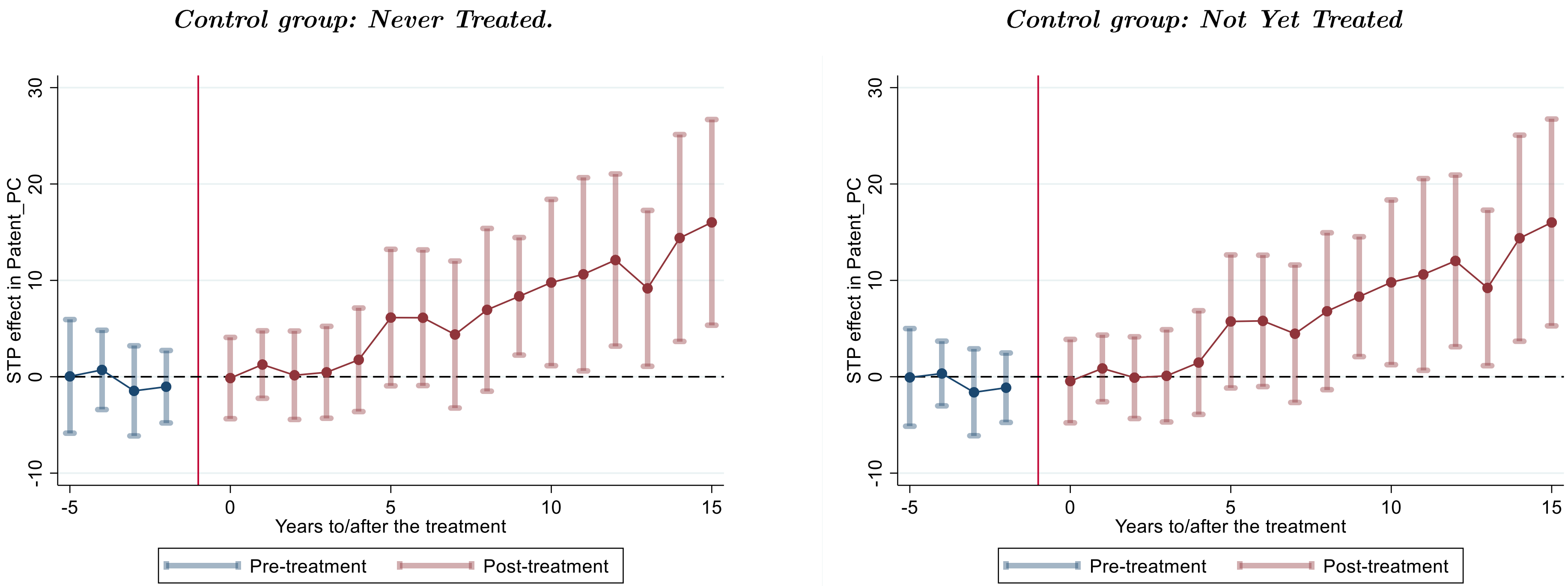


Figure 6. STP effect on patent intensity. Event study graphs excluding Madrid, Barcelona and treated provinces with less than 15 years of treatment.

Patent_PC as innovation indicator. Callaway and Sant'Anna (2021) method for DID models with panel data, using simple C&S estimator, implemented using csdid in Stata with the option long2 (using long differences for pre-treatment periods). Event time point estimates and 95% confidence intervals plotted. ATT stands for average treatment effect on the treated.

5. Further Analyses

Once, we have found that STPs show a positive effect on regional patents and this effect increases with time, we attempt to investigate the following research questions: Do these additional patents come at the expense of lower patent quality? Is the STP effect heterogenous according to province characteristicas and which is the portion of the effects that comes through the activity of tenants and which is the portion of the STP effect that comes through the activity of off-STP entities (that is, STP spillovers)?

5.1. Patent quality

Given the high heterogeneity in the value of patents (Gambardella et al., 2008; Scherer and Harhoff, 2000), the literature is paying increasing attention to patent quality (Higham et al., 2021), not only to patent counts. The previous analysis left unanswered the question about the quality of the patents generated due to the adoption of the STP policy, as rises in patent activity have been shown to lead to a straight decline in patent quality over time (van Zeebroeck and van Pottelsberghe de la Potterie, 2011). In other words, we aim to analyze whether the increase in patents in treated provinces come at the expense of a reduction in patent quality.

The more commonly used indicator for patent quality is the patent citations (Harhoff et al., 2003; Trajtenberg, 1990). We use the average 7-year citations per patent as the dependent variable to investigate whether the patents generated as a consequence of the adoption of the STP policy are of different quality. The utilization of this indicator has the consequence that we have to restrict our analysis to patents applied in 2012 at the most.[8]

[8] If we replicate the baseline analysis (Table 1) stopping in the year 2012 we find an average effect of STP slightly smaller than the one in the main analysis (the coefficients range from 3.98 to 4.75 depending on the specification, always statistically significant). The reason for this decrease in such replication is that a higher proportion of the estimated effects belong to the first years after the adoption of the STP policy (when the effect is still not fully revealed). Results are available upon request.

Results are shown in Tables 5 and 6 and Figures 7 and 8. Both show that average citations per patent are very similar for treated and untreated provinces, thus informing us that the additional patents generated by the STP policy are of similar quality.

Table 5. STP effect on patent quality

	Simple C&S	REG estimator	IPW estimator	DRIPW estimator
	(1)	(2)	(3)	(4)
	Cits7	Cits7	Cits7	Cits7
Park (NT)	-0.065 [0.129]	-0.058 [0.135]	-0.014 [0.157]	0.014 [0.139]
Park (NYT)	-0.092 [0.134]	-0.063 [0.137]	-0.021 [0.156]	-0.001 [0.143]
Control variables	NO	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
N	1650	1650	1650	1650

The dependent variable is average 7-year citations patents. Control variables: *GDPpc* and *unem*. NT stands for never treated. NYT stands for not yet treated. The effects are computed for the first 15 years after the adoption of the STP policy. * p < 0.10, ** p<0.05, ***p<0.01.

Column (1) shows the results for C&S without covariates. Column (2) shows the results for regression adjustment (REG) procedure estimator. Column (3) shows the results using Inverse Probability Weighting (IPW) to model the propensity score . Column (4) shows the results for doubly robust (DRIPW) estimator.

Table 6. STP effect on patent quality (subsample 15 years)

	Simple C&S	REG estimator	IPW estimator	DRIPW estimator
	(1)	(2)	(3)	(4)
	Cits7	Cits7	Cits7	Cits7
Park (NT)	0.038. [0.142]	0.021 [0.148]	0.007 [0.155]	0.028 [0.144]
Park (NYT)	0.045 [0.148]	0.050 [0.152]	0.025 [0.150]	0.037 [0.147]
Control variables	NO	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
N	1320	1320	1320	1320

The dependent variable is average 7-year citations patents. Control variables: *GDPpc* and *unem*. NT stands for never treated. NYT stands for not yet treated. The effects are computed for the first 15 years after the adoption of the STP policy and only the treated provinces observed at least for 15 years after the adoption of the STP policy are included * p < 0.10, ** p<0.05, ***p<0.01.

Column (1) shows the results for C&S without covariates. Column (2) shows the results for regression adjustment (REG) procedure estimator. Column (3) shows the results using Inverse Probability Weighting (IPW) to model the propensity score . Column (4) shows the results for doubly robust (DRIPW) estimator.

Control group: Never Treated. *Control group: Not Yet Treated*

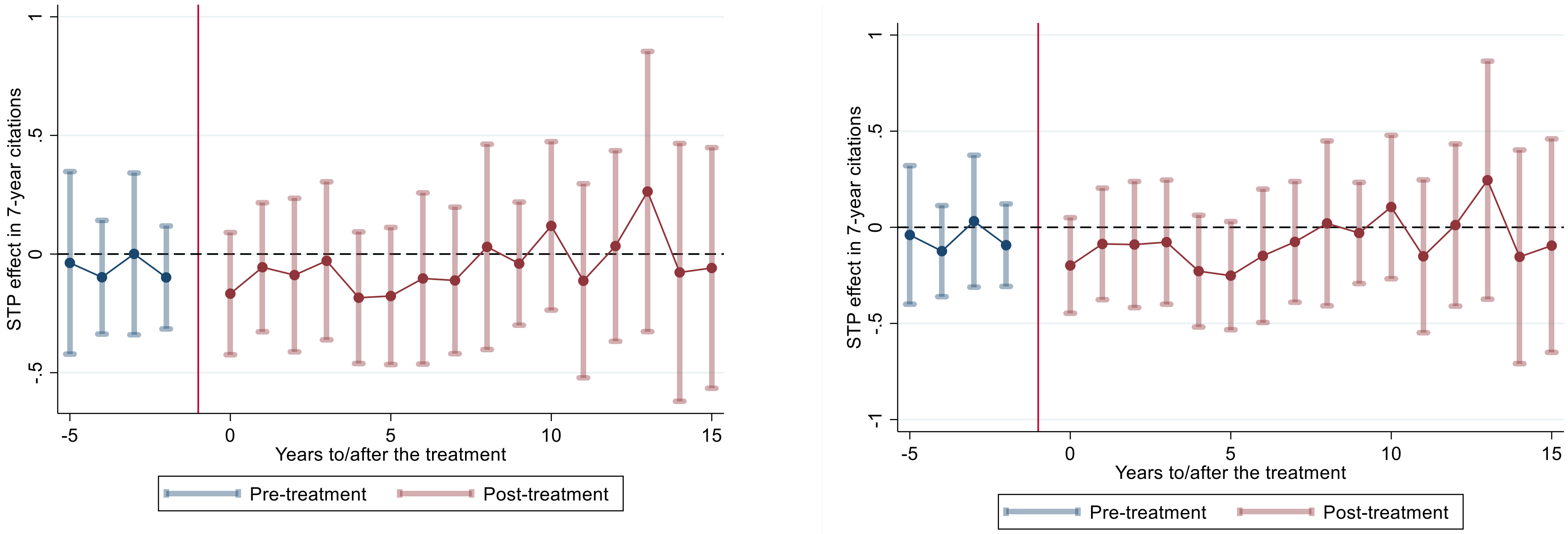


Figure 7. STP effect on patent citations. Event Study Graphs

Cits7 as innovation indicator. Patent_PC as innovation indicator. Callaway and Sant'Anna (2021) method for DID models with panel data, using simple C&S estimator, implemented using csdid in Stata with the option long2 (using long differences for pre-treatment periods). Event time point estimates and 95% confidence intervals plotted. ATT stands for average treatment effect on the treated

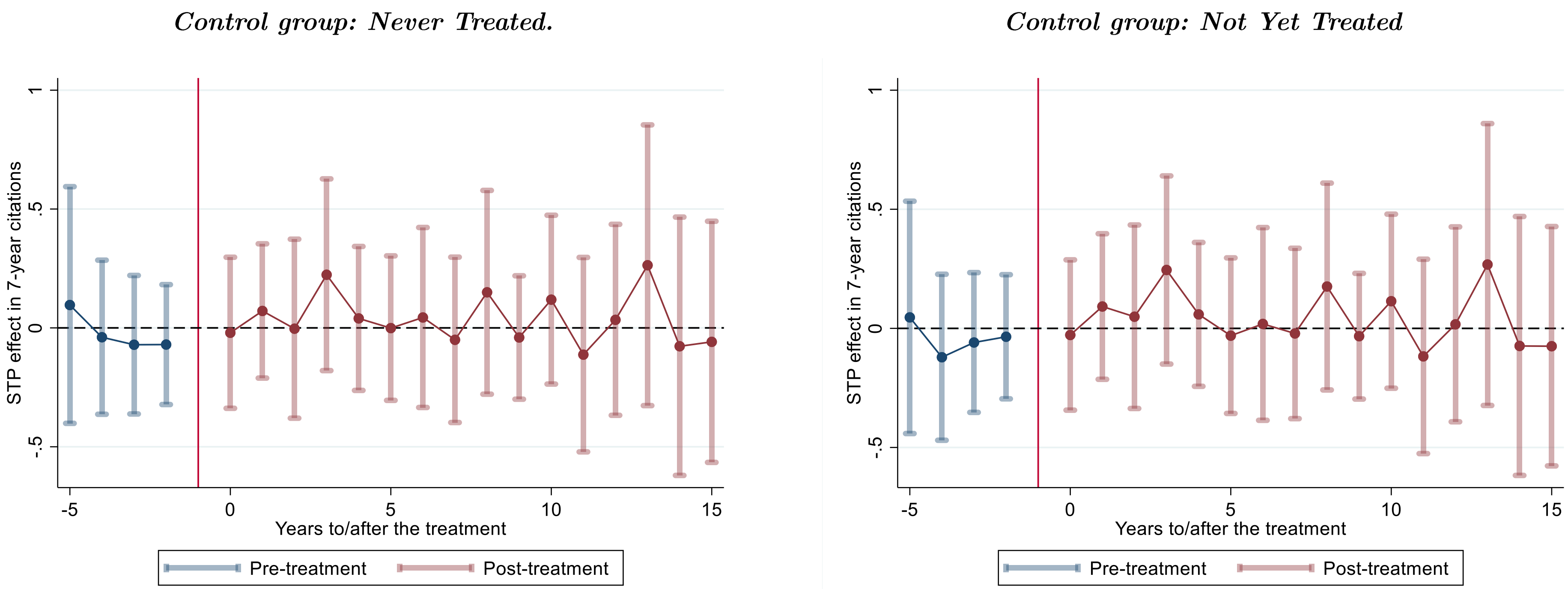


Figure 8. STP effect on patent citations. Event study graphs excluding treated provinces with less than 15 years of treatment. Cits7 as innovation indicator. Patent_PC as innovation indicator. Callaway and Sant'Anna (2021) method for DID models with panel data, using simple C&S estimator, implemented using csdid in Stata with the option long2 (using long differences for pre-treatment periods). Event time point estimates and 95% confidence intervals plotted. ATT stands for average treatment effect on the treated

5.2. Heterogeneous effects

In this section, we explore the heterogeneity of the STP effect.

To this aim, we make use of the set of 2x2 comparisons provided by the C&S method,[9] so that we regress the coefficients obtained for each treated province every year on several province characteristics and on the phase in which the STP was created, which could be potential sources of an heterogeneous effect of STPs.

Regarding province characteristicas, previous studies have suggested that STPs may show a higher impact in less advanced regions than in more advance ones (Albahari et al., 2018). To analyse if this has been the case, we include the following indicators for each province before the policy started in 1985: the average annual patents applied (*patents_pre*), which is an indicator for regional innovativeness, the average annual gdp per capita, in logs (*lgdp_pc_pre*) and the average unemployment rate (*unem_pre*), which are more general indicators of economic development.

Regarding the phase in which STPs were created, APTE distinguishes three different phases in the Spanish STP policy (APTE, 2008): An initial phase (1985-1992), where great emphasis was placed in urbanization projects with special attention to image, green areas and good communications. A development phase (1993-1998), with an increasing scientific orientation in the STPs created and the participation of the universities in some of the projects. Finally, an expansion phase (1999 onwards), with many provinces adopting the STP policy sometimes in collaboration with different agents, such as local governments or universities. Finally, we control for the size of the province, measured by the average population, in logs (*lpop_pre*) and also include year and duration fixed effects.

We restrict this analysis to treated provinces with at least 15 years of STP presence to avoid confounding heterogeneous effects with insufficient data in certain provinces. Table 7 shows the results of this analysis. Column 1 uses as dependent variable the 2x2 coefficients from C&S using NT as control group, while Column 2 uses the coefficient using NYT as control group. The results do not show any evidence of heterogeneous

[9] We take the coefficients from the model without covariates so that they are computed free from the influence of the provincial characteristics considered in this analysis of heterogeneous effects.

effects of STPs (beyond the dynamics of the effect that have been already highlighted and are controlled with the duration fixed effects). Having in mind that absence of evidence is not evidence of absence, we believe this result is of interest, especially for policymakers, as it underscores the horizontal nature of the STP policy able to achieve a similar effect in more or less developed regions.

Table 7. Analysis of heterogenous STP effects

	(1) NTCS	(2) NYCS
patents_pre	0.113	0.114
	[0.396]	[0.403]
lgdp_pc_pre	15.02	15.44
	[10.01]	[10.01]
lpop_pre	1.039	0.887
	[3.810]	[3.810]
unem_pre	25.07	27.06
	[48.67]	[49.21]
phase1	-15.74	-15.17
	[16.44]	[16.91]
phase2	-4.090	-3.374
	[9.566]	[9.905]
_cons	-18.99	-19.77
	[41.74]	[41.94]
N	330	330
r2	0.402	0.395

Standard errors are clustered by province. Population is measured in 1,000 inhabitants and GDP is per capita. Every OLS specification includes year and duration fixed effects. All treated provinces with at least 15 years of STP presence have been included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3. Spillover effects

An interesting question remains: which portion of the provincial STP effect is due to patents generated by STP tenants and which portion is due to patents generated by other organizations (STP spillovers)?

To address this question we proceed as follows:First, we have a set of year-province estimates of the STP effect (that is, of the patents generated due to the adoption of the STP policy). Second, if we can identify the number of patents generated by STP tenants in each province and year, we can calculate the percentage of the total STP effect attributable to STP tenants, with the remaining effect being attributed to spillovers.

To conduct such an analysis, we were able to identify the firm patents generated by STP tentant firms in the EPO dataset between 2004-2016,[10] which are the 15.6% on firm EPO patents in this period. The process followed to identify a firm patent as generated inside STP is explained in Appendix 1..

To have the set of year-province 2x2 DiD estimates of the STP effect on firm patents in the EPO dataset, we reestimate our baseline model using only EPO firm patents.[11]

Finally, to compute the percentage of the total STP effect due to patents by STP tenants and to STP spillovers, we consider only those STPs that are between 6 and 15 years old during the observed years, with the aim to have an homogeneous sample and to consider only the years for which we find a significant STP effect.

We find that spillovers account for approximately half of the effect. Specifically, 42.7% of the STP effect is explained by the patenting activity of STP tenants, while the remaining 57.3% is attributed to STP spillovers. These spillovers remain consistent over time, since for the periods 6-10 and 11-15 years, the percentage holds at 55.8% and 58.3%, respectively.

6. Conclusions

The interest in regional innovation policies has increased in recent years, with Science and Technology Parks (STPs) becoming one of the most widespread regional innovation policies worldwide. However, they have been seldom evaluated from a regional point of view. This paper estimates the regional effects of adopting the STP policy. To this aim,

[10] We could identify them by using the APTE directories which are not available before 2004. We rely on EPO patents only due to the fact that only 18% of PCT patents provide the postcode which is a key piece of information to classify patents as being generated inside STPs or not. Finally, we focus on firm patents because the criteria used to identify if a patent has been developed inside STPs cannot be applied to university patents, so that it was not possible to identify if a university patent was developed inside or outside the STP.

[11] Firm EPO patents are approximately 60% of total EPO patents between 2004 and 2016. To estimate the number of firm EPO patents before 2004, we applied this same percentage to the total number of EPO patents. Baseline results using this subsample of patents (available upon request) are very similar to the ones presented in Table 2.

we build a database of Spanish provincial data between 1980 and 2016 and apply a staggered differences-in-differences approach, taking advantage of the fact that the adoption took place over two decades and that not all the provinces have adopted the STP policy..

Our results report that the adoption of STP policy strongly affects the patenting activity of regions, which is revealed mainly in the medium term. More precisely, in years 6-10 after the adoption of the policy, the STP effect is around 49.8%; in years 11-15, it grows to approximately 79.7%. We have shown that these results are robust to the consideration of alternative methodological choices and assumptions. The robustness of our results is evidenced across all robustness checks carried out. We have considered the imposition of parallel trends conditional on some covariates, a subsample that includes only provinces with at least 15 years of STP adoption policy and, finally, the exclusion of Madrid and Barcelona due to their leading role in the Spanish economy and innovation production, shedding results that reinforce our baseline analysis.

We also conduct several additional analyses. First, we provide evidence that the additional patents generated by the STPs are of similar quality, measured by patent citations. Second, we analyse heterogeneous effects and do not find any evidence of heterogeneity according to provincial characteristics, suggesting that STPs are a horizontal policy that is able to produce an impact in different contexts. Finally, using the firm EPO patents, we explore which share of the STP effect is generated by tenants and which share can be attributed to STP spillovers benefitting local firms outside the STP. We conclude that around 57% of the effect is due to spillovers.

These results contribute to assessing STPs as a regional innovation policy and a better understanding of how STPs deliver their effect. On the one hand, this effect is not automatic (it takes around 5 years to observe a significant effect, still low in magnitude) and remarkably increasing in time, which links with the idea of 'patient capital' since the effects are revealed in the medium and long term (Mazzucato, 2015). On the other hand, the magnitude of the STP spillovers suggests that STPs show a large effect outside their boundaries and that the extensive literature on STP performance based on the comparison of similar firms inside and outside STPs might be underestimating the STP effect due to the fact that the control group used to build the counterfactual situation is, to an extent also treated.

Our work is not without limitations. First, patents are not the only relevant innovation indicator, but we did not find any other innovation indicator with a timespan large enough to conduct the analysis. Second, our study only relies on the Spanish case. Further studies in other countries and cross-country comparisons would be very useful. However, we can be cautiously confident about the generalisation of our results. Yet, Albahari et al. (2023), in their meta-analysis of STPs literature, find no significant country differences in the park effect. Third, we analyse the effect of the adoption of the STP policy, but we do not analyse the 'dose' of the policy. We believe this dose can be endogeneous as STPs working better will be more likely to grow than STPs working worse. Dealing with this endogenous dose is beyond the scope of this paper. Fourth, it could also be that the untreated provinces are, to some extent, treated. On the one hand, there could be some positive spillovers of STPs on geographically close provinces. On the other hand, it could also be that there exists some substitution effects due to firms moving from untreated to treated provinces. Fifth, our analysis of STP spillovers is restricted to firm EPO patents, so that we were not able to analyse the STP spillovers on university patents. These limitations also constitute an opportunity for further research.

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Appendix 1 – Descriptive statistics

Table A1. Descriptive statistics

Variables	Label	Mean	SD	Min	Max
Patents (per million inhabitants)	Patent_PC	14.64	23.59	0	166.38
GDP per capita (thousands of Euros)	GDPpc	13.18	7.73	1.35	37.68
Unemployment rate (%)	unem	16.92	7.69	2.23	45.12

Appendix 2 – Patent classification

We use two pieces of information that can serve to classify a patent as on-park or off-park: the address of the applicant (the firm) and the address of the inventors[12](see Figure A2).

First, if the address of at least one of the applicants is on-park and the address of at least one of the inventors[13] is on-park or nearby, i.e., located in the same region as the applicant, the patent is considered on-park (887 patent applications).

Second, if the address of at least one of the applicants is on-park but no inventor has an address in the park's region, the patent is considered an off-park patent despite having at least one on-park applicant. This is because the headquarters of a company may be located on-park and may be in charge of the administrative tasks related to patent filing, but if the research team that generated the patent is located off-park, the patent would be considered off-park according to our definition (14 patent applications).

Third, if none of the applicants' addresses belong to an STP but at least one address of the inventors belongs to a park, the patent would be considered on-park. This is done to take into account cases in which a patent is generated on-park but the company files it from an off-park office (154 patent applications).

Fourth, if none of the applicants' addresses belong to any STP and none of the inventors' addresses are on-park, the patent would be considered off-park except in one situation: if the applicant has their headquarters located in an STP in the same province reported in the patent application. If so, the patent is considered on-park. This would correspond to a case where a company has offices in the same

Each patent application has, on average, three inventors with an associated postal address for each.

[13] When there is no information on the address of the inventors but at least one applicant is on-park, we define that patent application as on-park.

province on- and off-park, and even though the patent is filed from the off-park office, it is very likely that the park played a role in achieving the patent (61 patent applications).

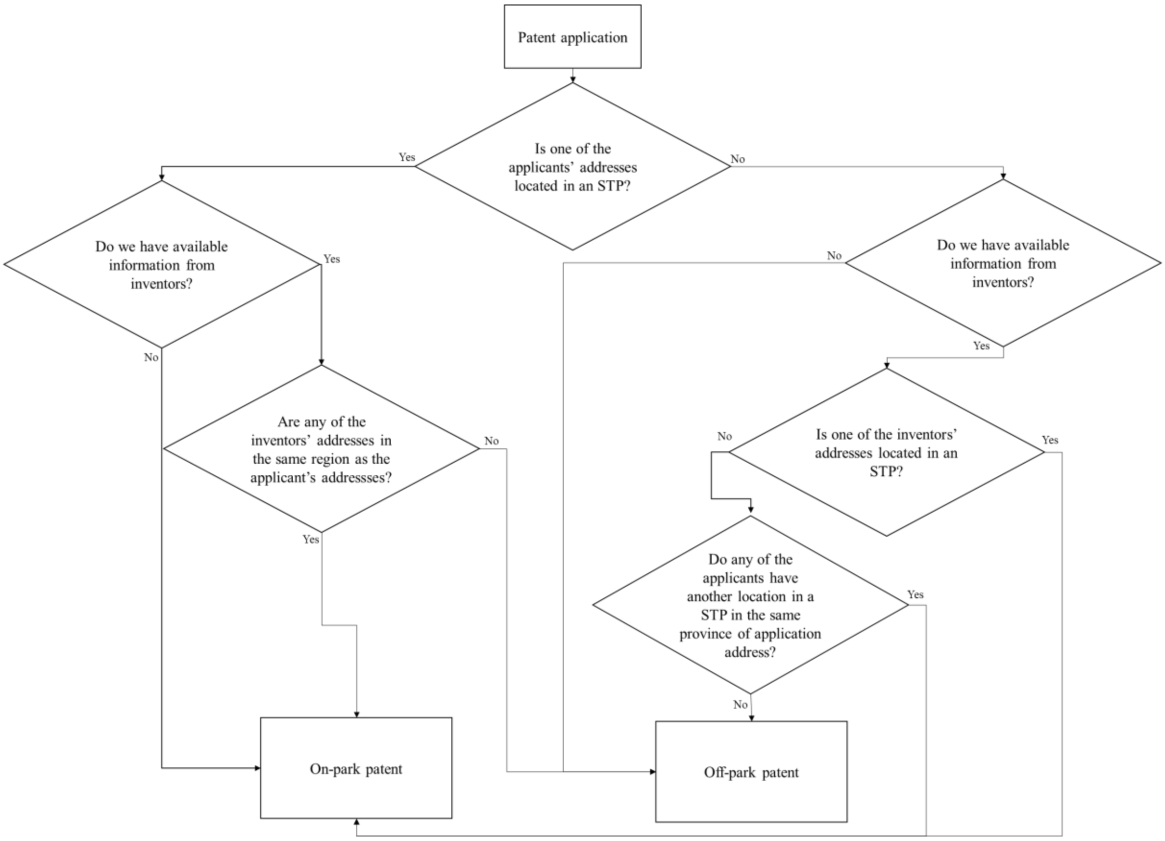

Figure A2. – Flowchart of patent classification