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Graphical Abstract

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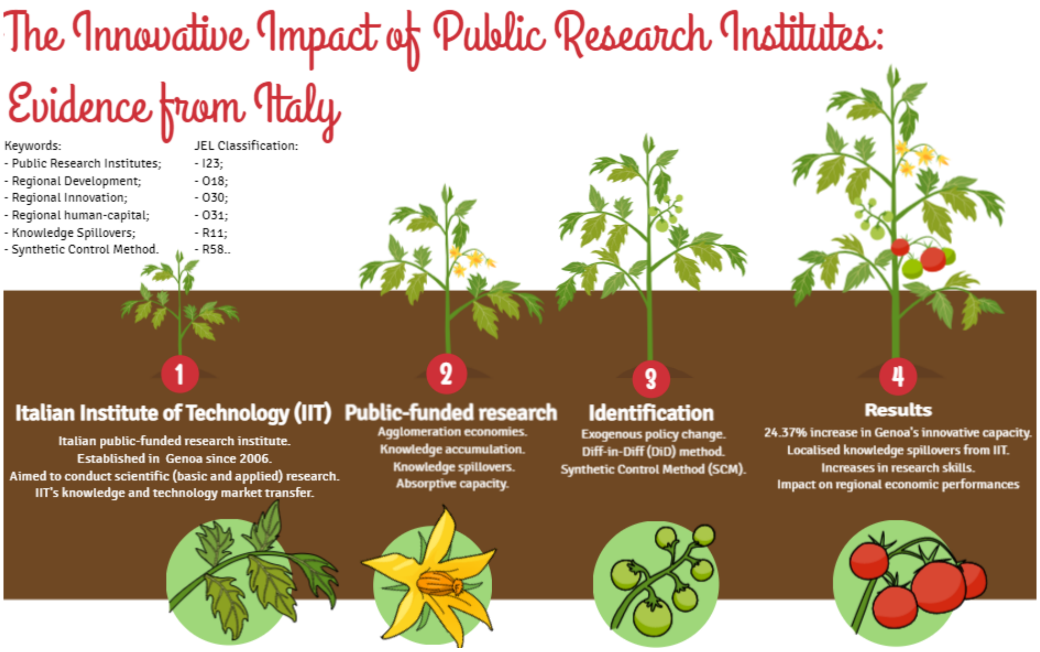

Highlights

The Innovative Impact of Public Research Institutes: Evidence from Italy

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The Innovative Impact of Public Research Institutes: Evidence from Italy

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Abstract

This paper leverages on the establishment of Italian Institute of Technology (IIT) as a policy change useful to understand the causal effect of public funded research centres on the regional innovative capacity. By relying on the Synthetic Control Method (SCM) approach and Italian NUTS-3 panel data, empirical results suggest that the establishment of IIT has positively impacted on regional innovation and high-skilled human-capital, as well as on regional growth. The paper also provides evidence of knowledge spillovers from IIT within the hosting region. Finally, these results are robust to a variety of placebo permutation tests as well as several sensitivity checks, or when considering a Difference-in-Differences (DiD) approach.

Keywords: Public Research Institutes, Regional Development, Regional Innovation, Regional Human Capital, Knowledge Spillovers, Synthetic Control Method

JEL: I23, O18, O30, O31, R11, R58

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1. Introduction

Nowadays, there is a widespread awareness that every country is characterised by large and persistent differences in regional economic performances (Iammarino et al., 2017). Policy-makers, among other policy tools, have tried to support deprived areas by establishing Public Research Institutes (PRIs), as new universities, large Research Infrastructures (RIs) and other public-funded research organisations (Reichert, 2019).[1] Indeed, the latter may support the development of a knowledge base and new technologies, thus generating competitive advantages for lagging regions through an innovation driven economic transformation (Duranton et al., 2015).

PRIs may contribute to innovation in a number of ways: (i) codified knowledge and knowledge embodied in technological innovations that are later taken up by firms, (ii) knowledge transfer and uptake through direct PRIs-firms collaborations, (iii) person-embodied knowledge and skills PRIs nurture. Specifically, innovation is primarily affected by new knowledge, and PRIs are traditionally involved in the process of generation, accumulation and transmission of the latter through a causal chain of effects between research investments, increases in the knowledge production infrastructure, creation of a (local) knowledge base, knowledge spillovers and economic agglomeration. This results in long-term growth in production and wealth. In addition, incentives for private R&D investments are often lower than the social optimum: hence, government programs to support regional innovation may be warranted.

[1] RIs are government-funded basic research centres aimed to expand the scientific and technological knowledge frontier, e.g. CERN.

From this perspective, last decades are characterized by the institution of various PRIs and knowledge transfer infrastructures in the EU, like the Institute of Science and Technology Austria (IST Austria, an international research institute established in 2009 to perform world-class basic research), the European Institute of Innovation and Technology (EIT, established in 2008 in order to support Europe's innovative ability), or the Human Technopole (HT, Italian research institute for life sciences established in 2016 to foster collaboration and bring added value to the scientific research ecosystem across Italy and Europe).

Therefore, given the broader trend of setting up such institutes across Europe, Counterfactual Impact Evaluation (CIE) analyses become crucial to understand whether the creation of such government-funded research institutions, among other possible policy tools, can stimulate regional innovation and growth. Nevertheless, the empirical literature is fragmented and limited. In particular, some authors focus on the economic impact of new universities (Cowan and Zinovyeva, 2013; Kantor and Whalley, 2014; Liu, 2015; Bonander et al., 2016; Valero and Van Reenen, 2019), generally highlighting agglomeration economies, local spillovers and rises in regional growth and productivity, while the impact of RIs and other public research institutions, to the best of knowledge, has been never provided using reliable CIE techniques.[2]

This study adds to the literature by leveraging on the Synthetic Control Method (SCM) approach and Italian NUTS-3 regional panel data in order to investigate the impact of Italian Institute of Technology (IIT) on innovative

[2]See Castelnovo et al. (2018), Castelnovo and Dal Molin (2020) and Bastianin et al. (2021).

performances of the Italian NUTS-3 region of Genoa.[3]

Established in 2003 (Law 326/2003) and active in Genoa since 2006, IIT is a public funded research institute that conducts scientific (basic and applied) research for purposes of technological development.[4]

Since its inception, IIT has attracted public funding of about €94 million each year, a significantly larger amount of government funding than the endowments of universities and other research institutions.[5] Such public funding is also relevant in relation to other contemporary Italian innovation policies, like the so-called technological districts (TD, similar to the French "Poles de Compétitivité") which received total public funds for 450 million euro without producing significant effects for firms involved in the program (Bertamino et al., 2016; Caloffi and Bellandi, 2017), or the strategy "Industria 2015", that provided about 23 million euro to innovative projects.[6]

Therefore, analyzing the impact on regional economic performances of such a relevant innovative policy can provide useful insights to policymakers in assessing the opportunity cost of public funding.[7] Moreover, notice that the establishment of IIT in Genoa has been the result of a political bargaining

[3]Terms "region" and "NUTS-3 region" will be used interchangeably to indicate Italian NUTS-3 statistical territorial units.

[4]Research takes place in Genoa and secondary labs in Turin, Milan, Rovereto, Pisa, Pontedera, Naples, Rome, Ferrara and Venice: however, the latter are quite smaller than the Genoa's central one. Appendix A provides detailed information on IIT.

[5]Source: `https://www.iit.it/documents/20123/223518/Relazione+Corte+dei+Conti+2019.pdf/232831c2-4796-145f-5289-fa7594822c68?t=1622033706731`

[6]See `https://trimis.ec.europa.eu/programme/industria-2015`.

[7]Given the significant amount of public funding absorbed by this innovative policy, as well as the peculiar characteristics of a hub for basic and applied research institutionally inherent in the institute under consideration, it seems justified to focus solely on the IIT, without considering other Italian and/or European PRIs.

process, thus representing an exogenous policy change useful to understand the effects of PRIs on regional economies.[8]

A fundamental concern in this work is the identification of an appropriate strategy to detect the innovative impact of IIT on the hosting region. In particular, the presence of only one treated region complicates the choice of a reliable control group, an issue that makes the identification of effects of interest very difficult to pin down.

Nearby regions are often used as controls, but this often blurs estimated results if these ones are heterogeneous along unobserved dimensions, typically related to geographical, social, political and economic characteristics. Moreover, Propensity Score Matching (PSM) is infeasible with a single treated unit. Further, a Difference-in-Differences (DiD) approach does not perform very well when policy changes are applied to a small number of treated units, thus making classical inference based on standard large-sample approximations misleading (Conley and Taber, 2011).

The SCM approach addresses these concerns by building, under certain assumptions that must be fulfilled, a synthetic control region, the so-called "synthetic Genoa", thus achieving a proper counterfactual for the treated region (Abadie et al., 2015). In particular, the synthetic control captures the development of the latter in the pre-treatment period relying on a weighted average of outcome and predictor variables of control regions. As a result, such synthetic control not only follows same pre-treatment trends as the treated unit, but even overlaps them, thus replicating outcome paths that

[8]See `https://www.ilsecoloxix.it/economia/2013/01/18/news/i-baroni-della-ricerca-all-assalto-dell-iit-1.32294420`.

Genoa would have experienced in the absence of the treatment and increasing the quality of impact estimation.[9] Hence, estimated divergences in outcome trajectories for Genoa and the synthetic one can be interpreted as the causal impact of the treatment.[10]

Empirical results provide evidence of a positive and significant impact of IIT on regional innovation. Conditioning on a set of predictor variables that should affect outcomes in regions both before and after the treatment, estimates suggest that, on average, IIT has led to a 24.37% increase in Genoa's innovative capacity, measured by fractional counting of patents, for each year after the implementation period (about 22.5 more patents for million inhabitants per-year). The paper also documents localised knowledge spillovers from IIT in the hosting region, which may be quantified, on average, in 16.86 more patents for million inhabitants per-year (18.43%).
Looking at other possible proxies for the innovative capacity, namely human-capital and knowledge base, estimates show how the intervention has triggered an increase in research skills, quantified in about 66 more inventors per million inhabitants every year than the synthetic one (34%). Lastly, evidence for a positive effect of IIT on per-capita GDP is also found.
Finally, given that for SCM estimators asymptotic inference cannot be performed, "in-space placebos" and "in-time placebos" are then proposed to assess the robustness of previous results. Indeed, the level of confidence about the

[9]Unlike DiD models, the SCM is also able to account for effects of possible confounders changing over time (Kreif et al., 2016).

[10]Main concerns in SCM approaches relates to the possible existence, contemporaneously to the time-period under investigation, of some confounding factors that may affect outcome variables, making the estimated impact biased. Comfortingly, other important innovation policies other than the IIT's establishment did not occur in Genoa.

validity of the latter would vanish if the SCM also estimated large impacts when implemented to years when the intervention did not occur or, alternatively, to regions that did not receive the treatment (Abadie et al., 2015). Comfortingly, paper's findings are robust to aforementioned placebo studies as well as to several sensitivity checks.

Main results might be due to several economic mechanisms, as agglomeration economies working through the attraction within the treated region of high-tech firms, high-quality researchers, PhDs and star scientists, those actors that larger benefit productivity and that uniquely have positive long-lasting effects on knowledge accumulation and knowledge spillovers (Waldinger, 2016). The development of formal competences and industrial liaisons, knowledge diffusion across space, knowledge and technology market transfer may also contribute to regional innovative processes. Moreover, knowledge sharing and specific training activities for scientific and research communities, as well as the networking with other research institutions, arguably improve knowledge dissemination, learning processes and effectiveness in transferring technologies, thus raising the ability to exploit new technological opportunities.

These results highlight relevant policy implications related to the appropriateness and effectiveness of the allocation of public resources to such kind of innovation policies. In particular, findings may provide some potential useful insights to inform policy-makers about marginal benefits of additional research funding, against which to compare opportunity-costs in terms of taxpayer money deployed and welfare losses attributable to taxation. Indeed, assessments of significant streams of private and social returns, i.e.

innovation, economic growth and general agglomeration economies, from public-funded research centres are essential to justify their financing.

The rest of the work is structured as follows. Section 2 describes related literature while Section 3 provides identification strategy and summary statistics. Empirical results are presented in Section 4, including robustness tests. Section 5 concludes.

2. Related Literature

This study fits with the literature related to the impact of public-funded universities, RIs or other public research institutes on innovation and regional growth. Indeed, innovation is primarily affected by new economic knowledge (Audretsch and Feldman, 1996) and such actors are traditionally emangmed players that originate and stimulate the transmission of the latter, thus contributing to industrial innovations (Mansfield and Lee, 1996; Anselin et al., 1997) and agglomeration economies.

Specifically, Nelson (1993), Goldstein et al. (1995) and Drucker and Goldstein (2007) emphasize mechanisms through which such institutions may impact on the regional economic development. Authors mainly refer to the support to technological innovation, attraction of other public/private capital investments, increases in the local knowledge production infrastructure, creation of a (local) knowledge base and development of high-skilled human-capital, which result in agglomeration economies.

Innovation is indeed supported by several common features of the local "milieu", i.e. presence of research institutes, clusters of high-tech firms and by any other characteristic that may promote knowledge spillovers, as local inter-firm alliances, mutual information and interactions between firms, researchers, scientists and specialised suppliers: the latter favour knowledge flows, the dissemination of tacit knowledge and learning processes, thus allowing knowledge exchanges of both formal and informal nature (Baptista, 1998; Feldman, 1999; Bennett et al., 2000; Love and Roper, 2001; Hervas-Oliver and Albors-Garrigos, 2009).[11]

As far as the empirical literature is concerned, some authors focus specifically on the impact of academic research (Cowan and Zinovyeva, 2013; Kantor and Whalley, 2014; Liu, 2015; Bonander et al., 2016; Valero and Van Reenen, 2019), while other ones deal with effects of large RIs (Castelnovo and Dal Molin, 2020; Castelnovo et al., 2018; Bastianin et al., 2021)

By relying on data for 20 Italian NUTS-2 regions between 1984 and 2000 and a first-difference estimation model, Cowan and Zinovyeva (2013) scrutinize whether the expansion of a university system affects local innovation. Authors highlight how regional patenting activity increases quite significantly even within five years of a new university opening, highlighting that lagging regions, those with low levels of R&D and human-capital investment, are the ones that benefit most from the intervention. Finally, they argue on the role of universities in filling gaps in missing R&D infrastructure.
By analysing US data from 1981 to 1996 and a IV approach, Kantor and Whalley (2014) find instead local spillovers from university research.[12] In

[11]Evidence of knowledge spillovers from academic research to firms' innovation can be found in Griliches (1986); Jaffe (1989); Berman (1990); Mansfield (1991); Martin (1998); Mansfield (1998); Tijssen (2002); Izushi (2003); Toole (2012).

[12]Authors instrument for overall university expenditure by exploiting differential impacts of stock price changes across counties where universities had different levels of endowments.

particular, authors highlight how the impact of universities on outcomes of interest is higher in the case of research-intensive universities or when the local productive fabric is technologically close to university researches.
Similar results can also be found in Liu (2015), who scrutinizes the effect of US land grant universities' establishment on several economic outcomes, relying on a panel of 1180 US counties from 1840 through 1940, an event study and a SCM approach. The author finds evidence of agglomeration economies, local spillovers from universities and huge increases in productivity.
While the latter focuses on effects of an historical intervention, Bonander et al. (2016) analyse the effectiveness of actual (1993-2011) Swedish research universities. In particular, authors examine the impact of granting research university status to three former university colleges on economies in different Swedish territories using regional panel-data for the period 1993–2011. Unlike Kantor and Whalley (2014) and Liu (2015), by applying a SCM approach authors find no effects of research universities on local economic and innovative performances, while they report positive effects in research competences.
Another fundamental contribution is that of Valero and Van Reenen (2019), which relies on regional-level patent-data and economic information for 38 countries in the 1978-2010 period. By implementing a five-year differences fixed-effects model, authors find that increases in universities' presence are positively correlated with higher regional per-capita GDP. Moreover, the paper suggests knowledge spillovers from universities to neighbouring regions.[13] They finally argue how the relationship between regional growth

[13] Also Moretti et al. (2019) may provide some interesting hints on the impact of public-funded R&D. In particular, by relying on data from 26 OECD countries in the 1987-2009

and universities may be driven by an increased supply of human-capital and greater innovation.[14]

Some other papers focus on economic spillovers from large RIs, providing evidence of significant technological externalities and increases in innovation (Scarrà and Piccaluga, 2020). Nevertheless, the unique research papers that apply econometric techniques to investigate the role played by RIs are those by Castelnovo et al. (2018), Castelnovo and Dal Molin (2020) and Bastianin et al. (2021).

The former, by observing 350 CERN's suppliers from 1991 to 2014 and leveraging on a CDM model, suggests that, after becoming suppliers, firms often exert a higher R&D effort and experience a rise in patenting. Moreover, they also show increases in labour productivity, revenues and margins.

Also Castelnovo and Dal Molin (2020) analyse the impact of RIs on performances of firms involved in their supply chain. By relying on a survey on a sample of Italian Institute for Nuclear Physics (INFN)'s suppliers (carried out between 2016 and 2017), logit models and a Bayesian network analysis, they suggest that suppliers' cooperation with INFN generates learning processes, increases in innovation, higher market penetration and networking benefits.

Lastly, Bastianin et al. (2021) focus on technology suppliers of CERN, observed over the 1995–2006 period, and scrutinize the time span needed for these firms to absorb the knowledge acquired during the procurement rela-

period and a IV approach, authors analyse the impact of public-funded R&D on private R&D investments and productivity, suggesting that public R&D "crowds-in" rather than "crowds-out" private R&D. Moreover, they find evidence in favor of a positive impact of public R&D on TFP as well as the presence of spatial spillovers.

[14]See also Beise and Stahl (1999); Aghion et al. (2009); Hausman (2012).

tion and develop it into a patent. By relying on count-data models, authors suggest that CERN have a positive and statistically significant effect on patent applications, with a delay of at least 5 years from the beginning of the procurement relationship.

This study contributes to the literature on the innovative impact of public-funded research centres in a number of ways.

First, the analysis provides empirical evidence on the regional innovative (and economic) impact of the IIT: in particular, following arguments in Drucker and Goldstein (2007), the paper finds support for almost all factors argued to be fundamental for the regional economy, i.e. creation of knowledge and human-capital, transfer of existing know-how, technological innovation and influence on the regional "milieu". Moreover, the study suggests significant local spillovers from such PRI within the hosting region.

Second, the paper provides a "methodological" contribution: while there exist studies on the economic impact of academic research, quantitative assessments of economic and innovative effects of non-academic public research institutions inferred from dependable techniques for causal inference, to the best of knowledge, have not been provided in the literature.[15] In particular, the paper is the first that analyzes the impact of such kind of research institutes leveraging on NUTS-3 regional data and a novel CIE identification strategy, the SCM, believing that such approach is the most reliable one to investigate the causal effect of economic shocks that are related to a specific region, while accounting for endogenous selection into the treatment.

[15] Empirical evidence from European research institutes other than universities is only provided without a causal interpretation of findings.

3. Data and Identification Strategy

3.1. Data

This paper relies on annual panel-data for 95 Italian NUTS-3 regions in 1980–2005 pre-intervention and 2006-2015 post-intervention periods (3420 observations).[16]

To assess the innovative impact of IIT on Genoa (as of 2006) the analysis primarily relies on a (per-capita) fractional count of patents as a measure of regional innovative performances. Indeed, as recognized by the economic literature, patents represent fundamental tools allowing the appropriation of the innovative activity; furthermore, innovative technologies with higher impact on social welfare and economic development are more likely to be patented (Pakes and Griliches, 1980). Finally, as argued by the innovation literature, patents are an effective measure of local technological capacity, although they do not measure all innovative activity (Smith, 2006) and not all inventions are patented.

Annual patent-data have been recovered for the period 1980-2015 from the European Patent Office (EPO)'s Patstat repository, that specifically refers to patent applications directly filed under the European Patent Convention or to patent applications filed under the Patent Co-Operation Treaty and designating the EPO (Euro-PCT).[17] In order to obtain a measure of regional

[16]Statistical areas considered in the analysis refer to Italian NUTS-3 regions. Since the number of the latter has been progressively changed in recent years, only 95 regions that have existed in 1980 have been considered.

[17]The database includes bibliographical and legal status patent-data from several countries at NUTS-3 regions level, as well as a detailed set of information on applications, applicants, inventors and their characteristics.

innovative performances, raw patent-data have been processed and aggregated at regional NUTS-3 level and the geographic distribution of patent applications has been assigned according to inventors' place of residence.[18] Data are limited to 2015 because of the existence of an underestimation for application counts in lastly years of coverage of the database, due to delays in the publication of EPO-data.[19]

Turning to other economic outcomes, the regional potential for innovation and per-capita GDP are considered. In particular, the dataset includes the number of inventors residing in each region; such measure, obtained from EPO-Patstat's raw patent-data, is well suited to be a proxy for the regional human-capital and knowledge base. Further, the paper explores the possibility that the innovative impact of IIT has spilled over to regional per-capita GDP as well. To this end, annual data are recovered from the "Urban Data Platform+" repository, described below.

To increase the comparability of treatment and control groups and to refine the quality of impact estimation, the analysis also leverages on a full set of control (predictor) variables referring to the university system, industrial performance indexes and economic indicators collected from the "Urban Data Platform+" repository.[20]

[18] If a patent is characterized by several inventors, the patent application is distributed equally between all of them and consequently between their NUTS-3 regions (fractional counting). The empirical analysis then necessitated adding a one to all patent and inventor count variables to allow for a logarithmic transformation that includes observations with zero values ($\log Innov_{i,t} = \log(Patents + 1)$ and $\log Inventors_{i,t} = \log(Inventors + 1)$).

[19] See Zuniga et al. (2009); Bronzini and Piselli (2016).

[20] Source: Joint Research Centre (JRC), Directorate General for Regional and Urban Policy (DG-REGIO), European Commission. `https://urban.jrc.ec.europa.eu/rel2018/\#/en/`.

Specifically, the number of active academic researchers, departments, universities and student enrolments, number of registered European trade-marks (ETM), Gross Value Added (GVA), Gross Fixed Capital Formation (GFCF), number of worked hours, compensation of employees and number of employed people are included in the dataset. Territorial-specific features, as population, surface and working-age population are also considered.[21]

Table 1 illustrates summary statistics on outcomes of interest and pre-intervention predictor variables for the overall sample (panel A), treated and control territories (panels B and C respectively); the latter are reported for the overall time-period, for the specific implementation year 2006 and for the last observational year 2015.

Further, Figure 1 provides Cumulative Average Growth Rates (CAGR) of the innovative capacity for Italian NUTS-3 regions in the ten-year pre-intervention period (left panel) and in the post-intervention decade (right panel). Notice that the left panel of Figure 1 shows how Genoa's innovation growth rate in 1995-2005 pre-intervention period is included in the second quintile, below the median of the sample distribution; CAGR in the post-intervention decade is instead included in the fourth quintile, which indicates that Genoa's innovative growth is at least higher than 60 percent of other regions' growth rates.

Finally, a caveat is important at this stage; aimed to scrutinize potential local knowledge spillovers from IIT to neighbouring firms, avoiding that the

[21]Notice that these have not all been included in the analysis, since only those endowed of great predictive power on outcomes of interest have been selected by the SCM algorithm (see Section 3.2).

innovative capacity of Genoa may potentially be driven only by IIT's direct patenting activities, the analysis also relies on a different sample. Specifically, in the latter all patents and inventors that refer to IIT have been identified and not considered in specific measures of innovation and regional human-capital. Notice that the paper will refer to the latter as the "*noIIT*" sample, while the main one will be denoted by the term "*Full*".

Table 1: Summary Statistics.

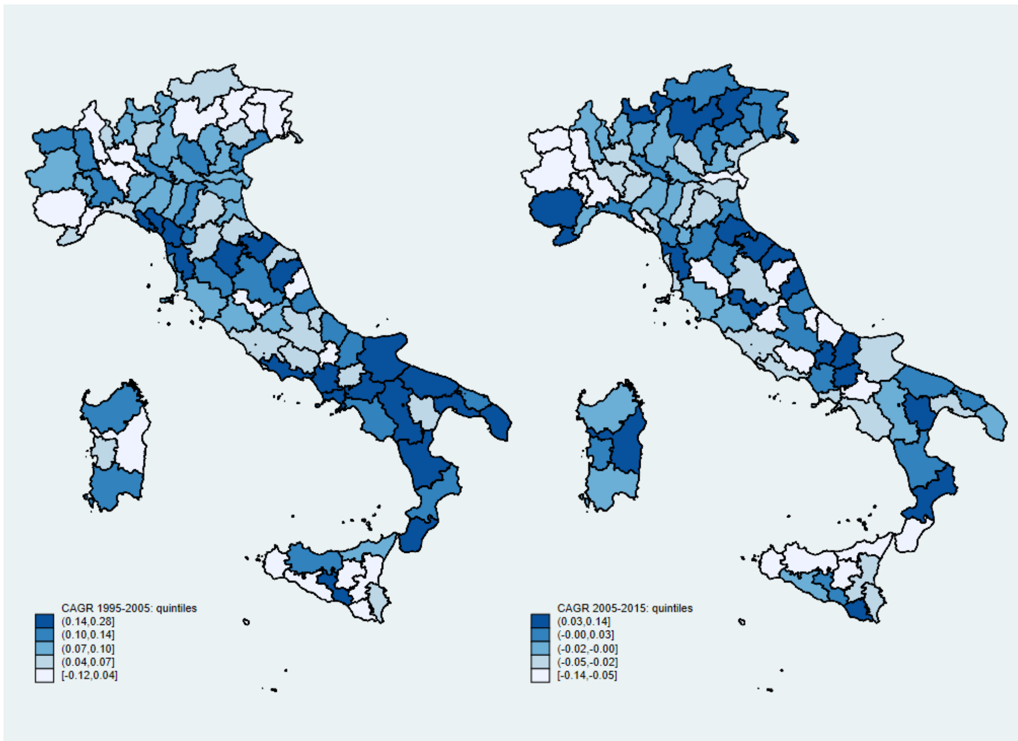
	(A) Overall Sample					
Variables	Mean	SD	2006	SD	2015	SD
Patents (Fractional Count)	32.77	70.69	53.00	97.12	45.85	72.74
Inventors (Number)	56.74	135.90	94.72	190.70	88.19	151.20
European Trade Marks (Number)	31.23	100.60	58.94	123.90	92.65	186.00
GDP (millions)	13,610.00	19,140.00	16,000.00	22,340.00	14,930.00	22,170.00
GVA (millions)	12,310.00	17,430.00	14,420.00	20,120.00	13,640.00	20,140.00
GFCF (millions)	16,930.00	12,810.00	22,010.00	16,340.00	15,740.00	12,400.00
Worked Hours (Number)	2,855.00	2,002.00	3,065.00	2,173.00	2,854.00	2,068.00
Compensations (millions)	30,310.00	27,600.00	40,710.00	32,280.00	44,530.00	37,250.00
Employed People (Number)	231,187.00	266,968.00	249,655.00	292,373.00	244,767.00	307,762.00
Population (Number)	570,284.00	588,493.00	577,414.00	596,769.00	600,171.00	642,943.00
Surface (sq. KM)	2,917.00	1,555.00	2,917.00	1,555.00	2,917.00	1,555.00
Working Age Population (Number)	376,573.00	392,059.00	378,534.00	397,547.00	387,225.00	420,848.00
Univerity Enrolments (Number)	18,135.00	34,499.00	19,136.00	35,734.00	-	-
Researchers (Number)	189.10	378.70	-	-	-	-
Universities (Number)	1.08	1.56	1.04	1.59	-	-
University Departments (Number)	5.73	8.21	6.14	9.03	-	-

	(B) Treated Unit					
Variables	Mean	SD	2006	SD	2015	SD
Patents (Fractional Count)	53.06	30.07	90.39	0.00	81.33	0.00
Inventors (Number)	100.40	67.95	165.00	0.00	204.00	0.00
European Trade Marks (Number)	36.50	41.34	77.00	0.00	112.00	0.00
GDP (millions)	23,600.00	2,442.00	26,410.00	0.00	24,670.00	0.00
GVA (millions)	21,690.00	1,866.00	23,790.00	0.00	22,390.00	0.00
GFCF (millions)	7,505.00	597.20	7,830.00	0.00	6,360.00	0.00
Worked Hours (Number)	1,189.00	49.63	1,193.00	0.00	1,097.00	0.00
Compensations (millions)	12,910.00	3,699.00	16,230.00	0.00	17,950.00	0.00
Employed People (Number)	371,892.00	14,727.00	381,142.00	0.00	387,330.00	0.00
Population (Number)	926,585.00	6,0407.00	876,579.00	0.00	861,253.00	0.00
Surface (sq. KM)	1,806.00	0.00	1,806.00	0.00	1,806.00	0.00
Working Age Population (Number)	571,323.00	4,6787.00	541,225.00	0.00	520,119.00	0.00
Univerity Enrolments (Number)	35,505.00	2,513.00	35,110.00	0.00	-	-
Researchers (Number)	503.90	150.00	-	-	-	-
Universities (Number)	1.35	0.49	1.00	0.00	-	-
University Departments (Number)	11.82	0.39	12.00	0.00	-	-

	(C) Donor-Pool					
Variables	Mean	SD	2006	SD	2015	SD
Patents (Fractional Count)	32.55	70.97	52.60	97.56	45.47	73.04
Inventors (Number)	56.28	136.40	93.97	191.50	86.96	151.60
European Trade Marks (Number)	31.18	101.00	58.74	124.60	92.45	186.90
GDP (millions)	13,500.00	19,210.00	15,880.00	22,430.00	14,830.00	22,270.00
GVA (millions)	12,210.00	17,500.00	14,320.00	20,210.00	13,550.00	20,230.00
GFCF (millions)	17,030.00	12,840.00	22,160.00	16,360.00	15,840.00	12,430.00
Worked Hours (Number)	2,872.00	2,005.00	3,085.00	2,176.00	2,873.00	2,071.00
Compensations (millions)	30,490.00	27,690.00	40,970.00	32,350.00	44,820.00	37,350.00
Employed People (Number)	229,641.00	268,017.00	248,210.00	293,662.00	243,200.00	309,098.00
Population (Number)	566,494.00	590,429.00	574,231.00	599,158.00	597,394.00	645,817.00
Surface (sq. KM)	2,929.00	1,559.00	2,929.00	1,559.00	2,929.00	1,559.00
Working Age Population (Number)	374,423.00	393,650.00	376,804.00	399,318.00	385,811.00	422,878.00
Univerity Enrolments (Number)	17,949.00	34,634.00	18,966.00	35,887.00	-	-
Researchers (Number)	185.80	379.00	-	-	-	-
Universities (Number)	1.08	1.57	1.04	1.60	-	-
University Departments (Number)	5.67	8.22	6.07	9.06	-	-

Notes: Summary statistics for 95 Italian NUTS-3 regions observed from 1980 to 2015. Panel A refers to the (*Full*) overall sample, panel B refers to Genoa (treated region), while panel C refers to remaining 94 regions (i.e the donor-pool). Descriptive statistics are reported for the overall time-period, for the specific implementation year 2006 and for the last observational year 2015.

Figure 1: Italian Patent Activity. Patent Fractional Count (growth rates).



Notes: Cumulative Average Growth Rates (CAGR) of the innovative capacity of Italian regions (*Full* sample). The left panel shows innovation growth rates for the 1995-2005 pre-intervention period. The panel on the right shows the same measure in the post-intervention decade.

3.2. The SCM Method

Since the location of IIT in Genoa as of 2006 have been influenced by many factors (arguably exogenous) other than economic considerations, this work identifies the latter as a policy change that allows to estimate the causal effect of PRIs on the regional innovative capacity.[22]

By applying the Synthetic Control Method (SCM), a combination of other

[22] See Appendix A.

unaffected Italian NUTS-3 regions (the so-called donor-pool) is designed to construct a “synthetic" control that mimics Genoa before the implementation of IIT, thus achieving a proper counterfactual (Abadie et al., 2015). Such donor regions are chosen by an algorithm that assigns weights on the basis of donors' resemblance to Genoa with respect to relevant predictive covariates and past realizations of outcomes of interest. As a result, such synthetic control not only follows same pre-treatment trends as the treated unit, but even overlaps them, thus replicating what Genoa would have experienced without IIT, increasing the quality of impact estimation and allowing to measure the causal impact of IIT in the post-intervention period.

Formally, 95 Italian NUTS-3 regions, among which region $j = 1$ is Genoa and units $j = 2,\ldots,95$ represent the donor-pool, are observed in years $t = 1980,\ldots,2015$, of which those before 2006 represent the pre-intervention period T_0, while the ones after 2006 constitute the post-intervention period T_1 ($T = T_0 + T_1$).

Assume that $W = (w_2,\ldots,w_{95})'$ is a (94×1) vector of weights, with $0 \leq w_j \leq 1$ for $j = 2,\ldots,95$ and $\sum_{j=2}^{95} w_j = 1$. Define then X_1 as the $(k \times 1)$ vector of pre-intervention characteristics of the treated region and X_0 as a $(k \times 94)$ matrix containing values of the same variables for the donor-pool. Let $Y_{j,t}$ be outcomes of region j at time t: in particular, consider $Y_{j,t}(1)$ as the $(T_1 \times 1)$ vector containing post-intervention values of outcomes of interest for the treated unit, while $Y_{j,t}(0)$ is the $(T_1 \times 94)$ matrix collecting post-intervention values of outcomes of interest for donor-pool units.

By considering two potential outcomes, namely $Y_{Genoa,t}(1)$ as outcomes of interest if Genoa at time t is exposed to the treatment and $Y_{Genoa,t}(0)$ if it does not, the treatment effect at time $t \in T_1$ is defined as:

$$\tau = Y_{Genoa,t}(1) - Y_{Genoa,t}(0) \tag{1}$$

Since $Y_{Genoa,t}(0)$ is unobserved, it is proxied by the SCM as a weighted average of donor-pool's regions, $j = 2, \ldots, 95$, the "synthetic control".
The set of optimal weights W^* characterises the synthetic Genoa so that best approximates the real one with respect to pre-intervention outcome predictors and a linear combination of pre-intervention outcomes. Optimal weights w_j^* are the ones that minimize $\sum_{m=1}^{k} \vartheta_m \left(X_{1,m} - X_{0,m} W\right)^2$, where ϑ_m reflects the relevance of predictor variables in accordance to their outcome predictivity. In particular, an optimal choice of such element is fundamental to minimize the Root Mean Squared Prediction Error (RMSPE) over the pre-intervention period.[23]
Therefore, the treatment effect for Genoa at time $t \in T_1$ is calculated as the difference between outcomes of the treated unit and its synthetic control:

$$\hat{\tau} = Y_{Genoa,t}(1) - \sum_{j=2}^{95} w_j^* Y_{j,t}(0) \tag{2}$$

The SCM has many advantages, both in terms of transparency and robustness of identification assumptions.
First, it is a useful econometric approach when only one region experiences the treatment. Indeed, while a comparison with nearby territories may provide biased estimated results if the latter are heterogeneous along un-

[23] RMSPE is aimed to measure the lack of fit between paths of outcomes for Genoa and its synthetic counterpart. It is defined as $\left(\frac{1}{T_0} \sum_{t=1}^{T_0} \left(Y_{1,t} - \sum_{j=2}^{J+1} w_j^* Y_{j,t}\right)^2\right)^{1/2}$.

observed dimensions, typically related to geographical, social, political and economic characteristics, a DiD approach does not perform well when treated units are limited to only one.[24] Likewise, although it is a suitable technique to choose from the donor-pool those units that are most similar to treated ones before the treatment, a PSM approach is nevertheless not feasible when there is only one treated unit.

Second, by implementing a weighted average of all controls, such method systematically offers more appealing comparisons with respect to DiD and other matching techniques. In particular, the control group is built according to a transparent data-driven process based on units that are alike in both observable and unobservable determinants of outcomes of interest, thus improving the quality of impact estimation and allowing for the presence of unobserved confounders that are not constant in time.

The SCM approach also has some limitations. The main concern relates to possible confounding policies, contemporaneous to the implementation of IIT, which may have influenced outcomes of interest, thus leading to biased impact estimates. Rather comfortingly, other important innovation policies, around 2006, which may have blurred the effect of IIT, did not occur in Genoa.[25] In particular, until 2015 the institution of IIT was arguably the

[24]The existence of a small number of groups providing information about treatment parameters of interest sometimes makes standard large-sample approximations used for inference not appropriate. This problem is exacerbated if standard errors are not corrected for small sample units (Conley and Taber, 2011).

[25]Italian enterprise and innovation policies, in last decades, have undergone a major change, i.e. the constitutional reform of 2001 that transformed Italy in a quasi-federal system; some competencies, including the majority of innovation policies, have been shared between regions and the Central Government on the basis of principle of vertical subsidiarity. While Caloffi and Bellandi (2017) ranked Liguria (and the region of Genoa) as territories adopting a minimalist model of intervention, thus resulting in a moderate innovative development

most prominent innovation policy which has ever been implemented in Italy, thus limiting this potential source of bias in our exercise.[26]

Finally, in studies applying SCM methods, asymptotic inference cannot be performed. Therefore, to address such concern "in-space" and "in-time" placebos, as well as sensitivity checks, are proposed.

4. Empirical Results

4.1. Impact on Regional Innovation

Regional innovative performances, measured by the (log) per-capita number of patents (fractional counting), are first considered.[27]

Despite being aware of concerns about such identification strategy, simple evidence is provided by estimating a DiD model to detect the innovative impact of IIT. The latter is built like $\log Innov_{i,t} = \alpha + \beta(Treated_{i,t} * Post_{i,t}) +$

and an absence of significant regional policies that could influence the results of the paper, the national innovative policies have been "lacking in terms of coordination between state, regional and local levels, persistency of orientation and funding, and relation to other public initiatives influencing the business context" (Caloffi and Bellandi, 2017), resulting mostly ineffective.

[26] National policies mainly focused on technological districts, resulted ineffective (Bertamino et al., 2016), the promotion of large-scale university-industry collaborations like the strategy “Industria 2015”, launched in 2006, but deleted in few years without results see `https://trimis.ec.europa.eu/programme/industria-2015`), or policies targeted to individual firms, like public guarantees. See Caloffi and Bellandi (2017) for an overview on firms and innovation policy in Italy. Moreover, it is worth noting that, according to the science journal Nature, IIT is ranked in the top 100 rising stars scientific institutes in the world; similarly, the scientific evaluation agency Anvur of Italy’s Ministry of Education evaluated and ranked the IIT as the top national scientific research centre. See `https://www.nature.com/articles/535S68a` and `https://www.anvur.it/wp-content/uploads/2019/03/105.IIT_.pdf`.

[27] A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero ($\log Innov_{i,t} = \log(Patents + 1)$ and $\log Inventors_{i,t} = \log(Inventors + 1)$).

$\mu_i + \tau_t + \epsilon_{i,t}$, where $\log Innov_{i,t}$ is our measure of innovative capacity and the parameter of interest, β, is associated to the interaction term between the dummy variable for Genoa and that for years after 2006. Region and year fixed effects, μ_i and τ_t respectively, are included.[28]

Another different specification includes lags à la Autor (2003) and is built like $\log Innov_{i,t} = \alpha + \sum_{j=0}^{5+} \beta_j (Treated_{i,t} * Post_{i,t+j}) + \mu_i + \tau_t + \epsilon_{i,t}$, in which $Post_{i,t+j}$ assumes value 1 in the specific year $t+j$ and 0 otherwise. The latter specification allows to scrutinize the possibility that treatment effects may speed up, stabilize, or mean revert over time.[29]

Table 2 shows DiD estimates (columns 1 and 2), while columns (3) and (4) report those for the specification that includes lags à la Autor (2003).[30] In particular, results in column (1) of Table 2 suggest a positive and statistically significant impact of IIT on Genoa's innovative performances, with an estimated effect of about 38%. Such result is confirmed when considering the estimation of the specification with lags à la Autor (2003) (columns 3 and 4) and when regions with main IIT secondary laboratories are excluded from the analysis (columns 2 and 4).

However, one should refrain from interpreting such results as a causal impact, due to aforementioned concerns related to DiD models (see Section 3.2). The SCM addresses these identification threats, building a reliable counterfactual that is characterized by a strong similarity in structural

[28] $Treated_{i,t}$ and $Post_{i,t}$ terms, since they are multicollinear with time and product fixed effects, are excluded as single regressors in the model.

[29] In order to lower the number of model's parameters, the effect of IIT is estimated from the implementation year ($t = 2006$) until five years later and onward ($t = 2011+$).

[30] Standard errors are clustered at Nuts-3 regional level.

Table 2: Impact of IIT on Innovation. DiD Estimates.

Dependent Variable: *Patents (log) per-capita*				
	(1)	(2)	(3)	(4)
$Genoa * Post_{2006}$	0.323***	0.318***		
	(0.0349)	(0.0348)		
$Genoa * Post_{2006}$			0.225***	0.221***
			(0.0371)	(0.0381)
$Genoa * Post_{2007}$			0.440***	0.435***
			(0.0459)	(0.0475)
$Genoa * Post_{2008}$			0.314***	0.312***
			(0.0441)	(0.0451)
$Genoa * Post_{2009}$			0.437***	0.433***
			(0.0462)	(0.0471)
$Genoa * Post_{2010}$			0.322***	0.312***
			(0.0426)	(0.0431)
$Genoa * Post_{2011+}$			0.299***	0.293***
			(0.0397)	(0.0395)
Regions FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Sample	*Full*	*Full*	*Full*	*Full*
IIT Secondary Labs	✓	✗	✓	✗
Observations	3,420	3,276	3,420	3,276
Adjusted R-squared	0.890	0.887	0.890	0.887
F Test (p-value)	0	0	0	0

Notes: Columns (1) and (2) show results of the estimation of a DiD model (*Full* sample). The dependent variable is (log) Patents (fractional count) per-capita and the variable of interest is the interaction term between the dummy variable for Genoa and that for years after 2006. The specification includes region and year fixed effects. Columns (3) and (4) show results from the estimation of a specification that includes lags à la Autor (2003). $Post_{i,t=2006,2007,...,2011+}$ assumes value 1 in the specific year t and 0 otherwise. Regressions in even columns do not include observations from regions that host main IIT secondary labs (Milan, Pisa, Turin and Rome). A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. Standard errors clustered at Nuts-3 regional level in parenthesis *** p<0.01, ** p<0.05, * p<0.1

characteristics with Genoa.

Table 3 shows region weights (left panel) and predictors balance (right panel). Specifically, patent activity trend in Genoa, prior to the implementation of IIT, is best reproduced by a combination of 16 Italian regions, those to which the SCM delivers positive critical weights. Moreover, in the right panel of Table 3, the value of the innovative output, as well as the set of predictor variables, of the treated region (Genoa) and the average of the synthetic one are reported (over the 26 years before IIT). As clearly shown, the synthetic Genoa closely mimics the real one both in terms of patents per-capita and in other predictor variables, thus confirming the goodness of SCM's matching properties.[31]

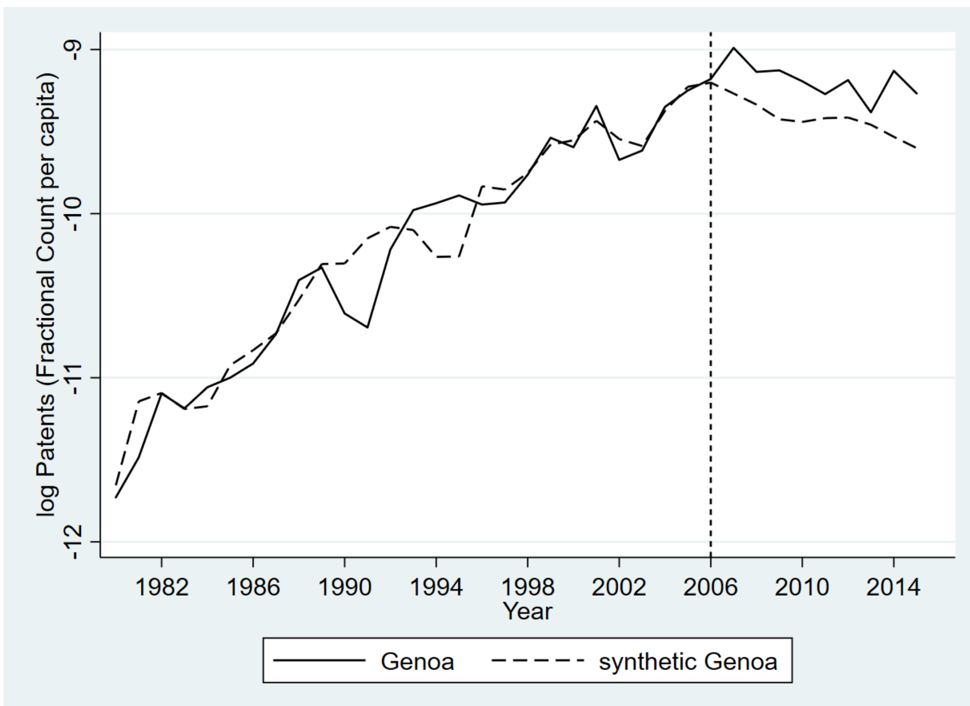
Table 4 depicts the magnitude of the impact of IIT on the innovative capacity of Genoa for the whole post-treatment period (2006-2015), while Figure 2 provides graphical evidence by comparing innovative trends of Genoa and the synthetic control over the 36-years sampling period.

The joint analysis of Figure 2 and Table 4 suggests that, on average, IIT has impacted on the innovative capacity of Genoa by about 22.5 more patents for million inhabitants every year (24.37%). In particular, causal effect estimates from Table 4 suggest annual gaps that range from 6.11 (7.53%) to 35.90 (39.69%) more patents per million inhabitants.[32] Results from Figure 2 suggest instead that the synthetic control closely matches the innovative

[31]Unlike other matching estimators, SCM prevents the estimation of "extreme counterfactuals", that are those that fall far outside the convex hull of the data (King and Zeng, 2006).

[32]The absolute effect is the total difference between the treated unit and the synthetic control one, while the relative effect is the absolute effect divided by the mean between real outcome and synthetic control estimate.

Figure 2: Impact of IIT on Innovation. Trends for Genoa and Synthetic Control.



Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual (*Full* sample). The weights used to build the synthetic control and the predictors balance are shown in Table 3. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero.

Table 3: Impact of IIT on Innovation. Predictors Balance and Region Weights.

Region	Weight	Predictors Balance	Treated	Synthetic
Aosta	.032	log Patents (per-capita 1980-2006 mean)	-10.239	-10.210
Avellino	.037	log Patents (per-capita 1996)	-9.945	-9.834
Brindisi	.007	log Patents (per-capita 1997)	-9.932	-9.853
Caserta	.038	log Patents (per-capita 1998)	-9.763	-9.752
Como	.100	log Patents (per-capita 1999)	-9.538	-9.579
Ferrara	.217	log Patents (per-capita 2000)	-9.595	-9.553
Foggia	.042	log Patents (per-capita 2001)	-9.344	-9.434
Milan	.022	log Patents (per-capita 2002)	-9.672	-9.546
Modena	.068	log Patents (per-capita 2003)	-9.616	-9.588
Naples	.032	log Patents (per-capita 2004)	-9.349	-9.374
Padua	.104	log Patents (per-capita 2005)	-9.249	-9.227
Palermo	.005	log Patents (per-capita 2006)	-9.180	-9.202
Pescara	.072	log Inventors (per-capita 1980-2006 mean)	-9.760	-9.760
Potenza	.034	log Inventors (per-capita 1996)	-9.334	-9.422
Siena	.048	log Inventors (per-capita 1997)	-9.486	-9.535
Vercelli	.140	log Inventors (per-capita 1998)	-9.408	-9.322
		log Inventors (per-capita 1999)	-9.059	-9.035
		log Inventors (per-capita 2000)	-9.062	-9.006
		log Inventors (per-capita 2001)	-8.904	-8.854
		log Inventors (per-capita 2002)	-9.023	-8.967
		log Inventors (per-capita 2003)	-9.089	-8.984
		log Inventors (per-capita 2004)	-8.728	-8.772
		log Inventors (per-capita 2005)	-8.593	-8.620
		log Inventors (per-capita 2006)	-8.578	-8.553
		log GDP (per-capita 1980-2006 mean)	10.095	10.088
		log GVA (per-capita 1980-2006 mean)	8.108	8.230
		Worked Hours (per-capita 1980-2006 mean)	.001	.008
		University Departments (million inhabitants 1980-2006 mean)	13.140	13.500

Notes: Predictors balance and region weights for the specification that analyses the innovative impact of IIT (*Full* sample). The SCM assigns critical weights in order to built a synthetic control that minimize the distance from the treated region in terms of innovative capacity and predictors of its subsequent growth. Such predictors are chosen in order to minimize the RMSPE. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero.

Table 4: Impact of IIT on Innovation. SCM Effect Estimates.

Year	log Patents - Treated (FC per-capita)	log Patents - Synthetic (FC per-capita)	Patents - Treated (FC million inhabitants)	Patents - Synthetic (FC million inhabitants)	Absolute Effect	Relative Effect
2007	-8.9896	-9.2681	124.70	94.39	30.31	27.67%
2008	-9.1361	-9.3356	107.71	88.23	19.48	19.89%
2009	-9.1270	-9.4251	108.69	80.67	28.02	29.59%
2010	-9.1934	-9.4410	101.71	79.40	22.32	24.64%
2011	-9.2717	-9.4180	94.05	81.25	12.80	14.60%
2012	-9.1863	-9.4144	102.43	81.54	20.89	22.71%
2013	-9.3828	-9.4581	84.16	78.05	6.11	7.53%
2014	-9.1296	-9.5318	108.41	72.51	35.90	39.69%
2015	-9.2676	-9.6004	94.44	67.70	26.73	32.98%

Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual (*Full* sample). The weights used to build the synthetic control and the predictors balance are shown in Table 3. The absolute effect is the total difference between treated and synthetic control units, while the relative effect is the absolute effect divided by the mean between real outcome and synthetic control estimate. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero.

evolution of Genoa in the pre-intervention period, except for a small period

(1990-1994) not in proximity to the intervention.[33] Specifically, after 2006, innovative trends of the treated region and the synthetic control start to significantly diverge, with a sudden increase of Genoa with respect to its synthetic counterpart. From 2008 to the end of the sample period such positive impact does not vanishes, although the trend is reversed; nevertheless, even in the second half of the sampling period the real Genoa shows higher innovation levels than the synthetic one, thus suggesting a large positive effect of IIT on per-capita patent applications.[34]

These empirical findings can be explained by main predictions of the innovation literature. Indeed, it is widely recognised that new knowledge is a key driver of innovation. In particular, IIT may have increased the local knowledge production infrastructure, arguably favouring the process of exploratory search and the creation of a (local) knowledge base, by engaging in more basic and risky research. Moreover, two of IIT's primary goals are to transfer own technology research results to the productive fabric and to support the creation of new start-ups and researchers' spin-offs; this further favours knowledge accumulation, agglomeration economies working through the attraction of high-skilled human-capital and high-tech firms within the region, and spillover effects, which in turn spur innovation. Finally, IIT also supports a variety of knowledge sharing activities, aimed to foster

[33] It is worth noting that predictors in the model are chosen in order to minimize the RMSPE: to alleviate concerns about the bad match during the 1990-1994 period, Section 4.1.2 provides an in-depth robustness analysis.

[34] Results are aligned to those in Cowan and Zinovyeva (2013), Kantor and Whalley (2014), Liu (2015), Valero and Van Reenen (2019), Moretti et al. (2019) Castelnovo and Dal Molin (2020) and Bastianin et al. (2021). Notice that estimates could also be seen as contradictory with respect to Bonander et al. (2016). However, this divergence can easily be explained by the different nature inherent in the institutions under scrutiny.

knowledge dissemination, and training activities for researchers and the scientific community, spanning from Ph.D. programs to the research and networking with other research organizations; such activities may favour the transmission, transformation, absorption and utilization of the regional knowledge base, raising firms' absorptive capacity, that is fundamental in fostering innovation (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998; Lane et al., 2001).[35]

4.1.1. Measuring Spillover Effects from IIT

By leveraging on the *noIIT* sample, this Section seeks to prove spread knowledge effects of IIT to neighbouring firms. In particular, by dropping patents that are directly filed by IIT and preserving remaining industrial ones, this exercise allows to disentangle spillover effects from the direct impact of IIT on patenting. Moreover, one addresses concerns about the possibility that main results may be driven by IIT's own patent activity, an issue that might blur results in Section 4.1.

Some preliminary evidence is provided in Table 5 by adopting a DiD strategy (columns 1 and 2) and a specification that includes lags à la Autor (2003) (columns 3 and 4).[36]

In particular, findings from this analysis confirm a positive and significant impact of IIT on innovative performances of Genoa (about 31%), even if observations from regions hosting main IIT secondary labs are excluded (even

[35]Notice that findings may be in part the result of spatial reorganization of economic activities. However, in the construction of the synthetic Genoa positive weights are never assigned to neighbouring regions, alleviating this concern.

[36]Models are built like in Section 4.1. Standard errors are clustered at Nuts-3 regional level.

Table 5: Knowledge Spillovers from IIT. DiD Estimates.

Dependent Variable: *Patents (log) per-capita*				
	(1)	(2)	(3)	(4)
$Genoa * Post_{2006}$	0.270***	0.265***		
	(0.0346)	(0.0346)		
$Genoa * Post_{2006}$			0.225***	0.221***
			(0.0371)	(0.0381)
$Genoa * Post_{2007}$			0.441***	0.436***
			(0.0458)	(0.0474)
$Genoa * Post_{2008}$			0.301***	0.300***
			(0.0441)	(0.0450)
$Genoa * Post_{2009}$			0.416***	0.412***
			(0.0462)	(0.0471)
$Genoa * Post_{2010}$			0.295***	0.285***
			(0.0425)	(0.0430)
$Genoa * Post_{2011+}$			0.205***	0.199***
			(0.0394)	(0.0391)
Regions FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Sample	*noIIT*	*noIIT*	*noIIT*	*noIIT*
IIT Secondary Labs	✓	✗	✓	✗
Observations	3,420	3,276	3,420	3,276
Adjusted R-squared	0.891	0.887	0.890	0.887
F Test (p-value)	0	0	0	0

Notes: Columns (1) and (2) show results of the estimation of a DiD model (*noIIT* sample). The dependent variable is (log) Patents (fractional count) per-capita and the variable of interest is the interaction term between the dummy variable for Genoa and that for years after 2006. The specification includes region and year fixed effects. Columns (3) and (4) show results from the estimation of a specification that includes lags à la Autor (2003). $Post_{i,t=2006,2007,...,2011+}$ assumes value 1 in the specific year t and 0 otherwise. Regressions in even columns do not include observations from regions that host main IIT secondary labs (Milan, Pisa, Turin and Rome). In the *noIIT* sample all patents referring to IIT have been identified and dropped from the analysis. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. Standard errors clustered at Nuts-3 regional level in parenthesis *** p<0.01, ** p<0.05, * p<0.1

columns) or when the specification with lags à la Autor (2003) is considered.

In order to address DiD's identification threats the SCM is performed. Results are shown in Figure 3 and Table 7, while Table 6 provides predictors balance and region weights.

Table 6: Knowledge Spillovers from IIT. Predictors Balance and Region Weights.

Region	Weight	Predictors Balance	Treated	Synthetic
Aosta	.032	log Patents (per-capita 1980-2006 mean)	-10.239	-10.210
Avellino	.037	log Patents (per-capita 1996)	-9.945	-9.834
Brindisi	.007	log Patents (per-capita 1997)	-9.932	-9.853
Caserta	.038	log Patents (per-capita 1998)	-9.763	-9.752
Como	.100	log Patents (per-capita 1999)	-9.538	-9.579
Ferrara	.217	log Patents (per-capita 2000)	-9.595	-9.553
Foggia	.042	log Patents (per-capita 2001)	-9.344	-9.434
Milan	.022	log Patents (per-capita 2002)	-9.672	-9.546
Modena	.068	log Patents (per-capita 2003)	-9.616	-9.588
Naples	.032	log Patents (per-capita 2004)	-9.349	-9.374
Padua	.104	log Patents (per-capita 2005)	-9.249	-9.227
Palermo	.005	log Patents (per-capita 2006)	-9.180	-9.202
Pescara	.072	log Inventors (per-capita 1980-2006 mean)	-9.760	-9.760
Potenza	.034	log Inventors (per-capita 1996)	-9.334	-9.422
Siena	.048	log Inventors (per-capita 1997)	-9.486	-9.535
Vercelli	.140	log Inventors (per-capita 1998)	-9.408	-9.322
		log Inventors (per-capita 1999)	-9.059	-9.035
		log Inventors (per-capita 2000)	-9.062	-9.006
		log Inventors (per-capita 2001)	-8.904	-8.854
		log Inventors (per-capita 2002)	-9.023	-8.967
		log Inventors (per-capita 2003)	-9.089	-8.984
		log Inventors (per-capita 2004)	-8.728	-8.773
		log Inventors (per-capita 2005)	-8.593	-8.620
		log Inventors (per-capita 2006)	-8.578	-8.553
		log GDP (per-capita 1980-2006 mean)	10.095	10.088
		log GVA (per-capita 1980-2006 mean)	8.108	8.230
		Worked Hours (per-capita 1980-2006 mean)	0.001	0.008
		University Departments (million inhabitants 1980-2006 mean)	13.140	13.500

Notes: Predictors balance and region weights for the specification that analyses knowledge spillovers from IIT to neighbouring firms (*noIIT* sample). The SCM assigns critical weights in order to built a synthetic control that minimize the distance from the treated region in terms of innovation and predictors of its subsequent growth. Such predictors are chosen in order to minimize the RMSPE. In the *noIIT* sample all patents referring to IIT have been identified and dropped from the analysis. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero.

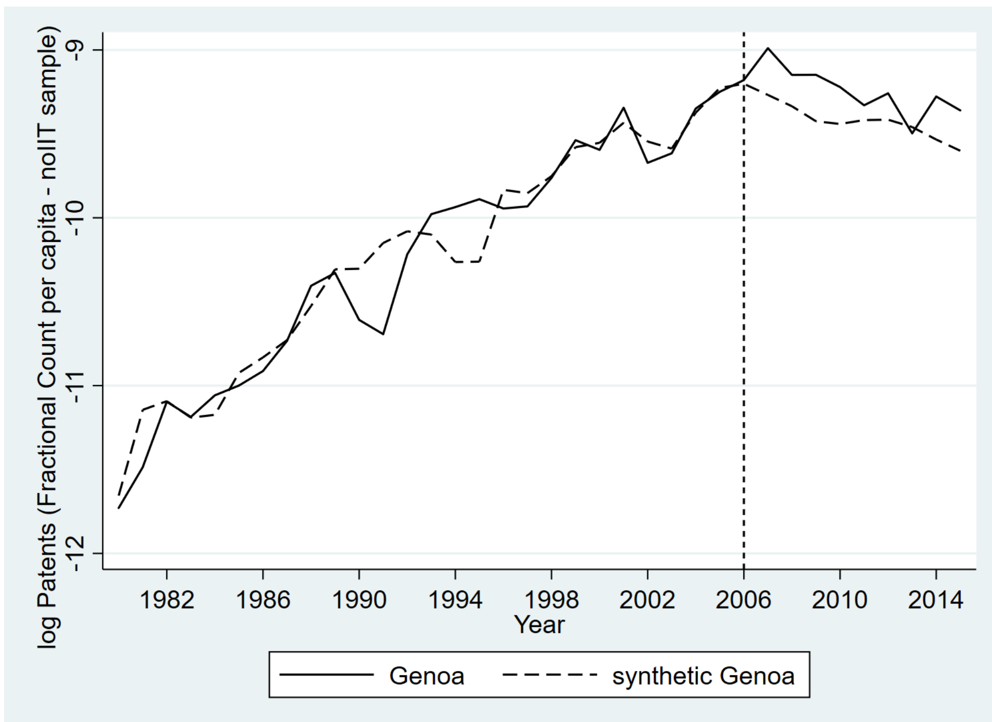
Table 7: Knowledge Spillovers from IIT. SCM Effect Estimates.

Year	log Patents - Treated (FC per-capita)	log Patents - Synthetic (FC per-capita)	Patents - Treated (FC million inhabitants)	Patents - Synthetic (FC million inhabitants)	Absolute Effect	Relative Effect
2007	-8.9896	-9.26810	124.70	94.39	30.31	27.67%
2008	-9.1489	-9.3356	106.33	88.23	18.11	18.61%
2009	-9.1483	-9.4251	106.40	80.67	25.72	27.50%
2010	-9.2210	-9.4410	98.93	79.40	19.54	21.91%
2011	-9.3298	-9.4180	88.74	81.25	7.50	8.82%
2012	-9.2583	-9.4155	95.31	81.45	13.86	15.69%
2013	-9.4971	-9.4595	75.07	77.94	-2.87	-3.76%
2014	-9.2774	-9.5337	93.52	72.37	21.15	25.50%
2015	-9.3603	-9.6007	86.07	67.68	18.39	23.93%

Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual (*noIIT* sample). The weights used to build the synthetic control and the predictors balance are shown in Table 6. The absolute effect is the total difference between the treated and the synthetic control units, while the relative effect is the absolute effect divided by the mean between real outcome and synthetic control estimate. In the *noIIT* sample all patents referring to IIT have been identified and dropped from the analysis. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero.

In particular, regarding the quality of fit in the pre-intervention period,

Figure 3: Knowledge Spillovers from IIT. Trends for Genoa and Synthetic Control.



Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual (*noIIT* sample). The weights used to build the synthetic control and the predictors balance are shown in Table 6. In the *noIIT* sample all patents referring to IIT have been identified and dropped from the analysis. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero.

nothing appears to have significantly changed. Moreover, predictors balance (Table 6) remains reasonably similar in the treated region and the synthetic version for all pre-treatment predictor variables.
The joint analysis of Table 7 and Figure 3 suggests that, after the creation of IIT, Genoa have had about 16.86 more additional patents per millions inhabitants every year (18.43%); moreover, outcome's trends are quite similar to those previously analysed. In particular, effect estimates range from 7.50 (8.82%) to 30.31 (27.67%) more patents every million inhabitants: these results provide evidence (despite the smaller magnitude) of a positive and significant impact of IIT on the innovative capacity of Genoa, thus confirming results in Section 4.1 and reinforcing the idea of knowledge spillovers to the regional productive fabric.

Therefore, public research centres are confirmed to be a fertile learning environment for neighbouring firms (Autio et al., 2004), due to several economic mechanism, as agglomeration economies and the attraction of high-skilled human-capital and high-tech firms within the treated region (see Section 4.2). Moreover, the proximity of firms from different industries to IIT, just as the variety of technology transfer to the market and knowledge sharing activities implemented by IIT, arguably affect how well knowledge spreads among such players to facilitate innovation as well as firms' absorptive capacity: in turn, the latter may increase the stock of knowledge which allows the exploitation of new technological opportunities, thus further enhancing regional innovation.

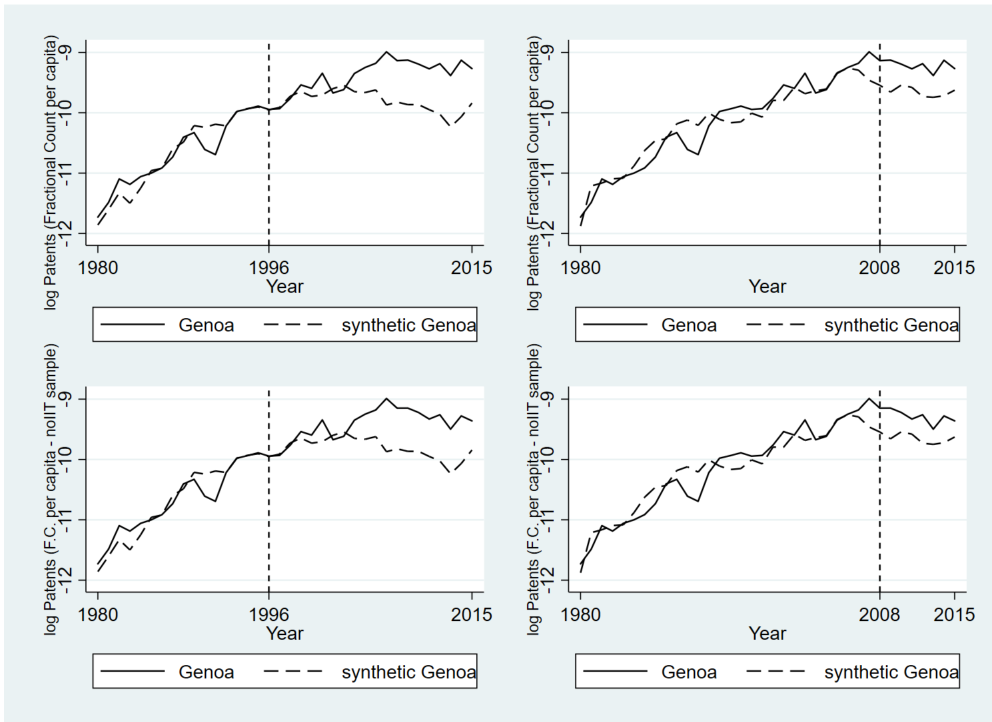
4.1.2. Robustness Analysis

In this Section an extensive robustness analysis, through different falsification and placebo tests, is provided.
Specifically, "in-space placebos" and "in-time placebos" are proposed. Indeed, the level of confidence about paper's findings would vanish if the SCM also estimated large impacts when implemented to years when the intervention did not occur or, alternatively, to regions that did not receive the treatment (Abadie et al., 2015).

First, "in-time placebos" involve performing main specifications by shifting the timing of the treatment in *fake* years 1996 and 2008. Indeed, in 1996 Genoa should not be affected by IIT, and a placebo estimate differing significantly from the pre-treatment path observed in Section 4.1 would call the model's predictive power into question (McClelland and Gault, 2017).
Differently, by moving the treatment timing in 2008 the analysis seeks to deepen the theme of a possibly effect lag: in fact, although the analysis in Figure 2 shows that the impact of IIT is tangible from the first year of implementation, i.e. 2006, it is not possible to exclude that this result may be biased by a lack of predictive power of the model, not highlighting the correct timing between the establishment of the IIT and the generation of its innovative effects.[37] Once again, any discovered impact of IIT with such specification should be suspicious, casting some doubts on effects found in the main analysis.

[37] If one considers the time needed to absorb knowledge flows and implementing learning processes, it is reasonable to think that the impact of ITT would show up only some years after its establishment.

Figure 4: Impact of IIT on Innovation in *Fake* Years. Trends for Genoa and Synthetic Control.



Notes: Innovative capacity, proxied by log Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual. *Fake* years of the treatment are assumed to be 1996 (left panels) or 2008 (right panels). In the *noIIT* sample all patents that refer to IIT have been identified and dropped from the analysis. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. Effect estimates, predictors balance and weighting matrix, not reported, are available on request.

Figure 4 shows results for the *fake* implementation year 1996 in left panels, while those for the *fake* implementation year 2008 are presented in right ones. Bottom panels rely instead on the *noIIT* sample.[38] Reassuringly, no direct effects of IIT on the innovative capacity of the treated region in *fake* year 1996 are detected; on the other hand, by considering right panels, the analysis excludes possible effect lags, thus corroborating the validity of the

[38]Predictors balance and region weights are available on request.

research design adopted for Section 4.1.

Second, "in-space placebos" are proposed. In particular, the latter involve performing main specifications after an artificial redistribution of the treatment to regions not exposed to the intervention. In every reiteration of the SCM one estimates placebo impacts for every potential control region, achieving a distribution of placebo effects, i.e. assessing the distribution of the test statistic under the null hypothesis of no treatment effect. The rationale is to reassess the pseudo-effect of IIT on untreated regions compared to the actual effect on Genoa: the level of confidence that the intervention has led to an effect on outcomes of interest would be undermined if the magnitude of the estimated impact fell well inside the core of the distribution of placebo effects.[39] If this is the case, the SCM does not provide good predictions of outcomes' trajectories.

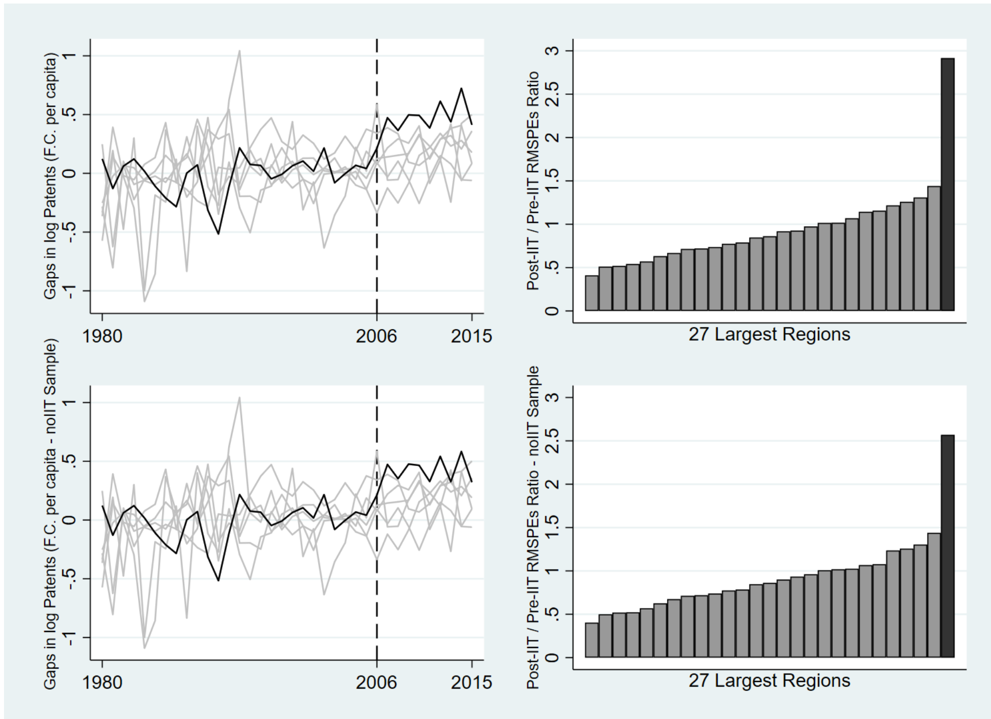
Results of this test are presented in Figure 5 (left panels).[40] Black lines show estimated gaps between outcomes of interest for Genoa and its synthetic control, while grey lines represent same gaps related with each iteration of the placebo test.[41] Reassuringly, estimated outcomes differences for Genoa during the 2006–2015 post-implementation period seem to be abnormally large with respect to the distribution of placebo gaps.

[39]Under the null hypothesis of no intervention effect, the estimated impact of the intervention is not expected to be abnormal with respect to the distribution of placebo effects.

[40]Following Bronzini et al. (2020), the placebo study is restricted to the largest 27 regions, those endowed of an average population above 570284 inhabitants, i.e. the regional average population over the sampling period.

[41]Although the placebo exercise has been conducted for all 27 regions with an average population above 570284 inhabitants, for reasons of graphical representation only outcome gaps for Genoa and the 6 regions most similar in terms of population, namely Bergamo, Florence, Bologna, Padua, Caserta, and Venice, are shown. Appendix B provides detailed graphs of this inferential exercise (all 27 outcome gaps), based on which comments refer.

Figure 5: Inference. Placebo Gaps and Post-IIT/Pre-IIT RMSPEs Ratios.



Notes: Left panels provide inference analysis for the SCM approach, showing gaps between outcomes in treated (placebo) regions and corresponding synthetic ones. Genoa (black line) and 26 regions (those endowed of an average population above 570284 inhabitants) as placebo. For reasons of graphical representation only outcome gaps for Genoa and the 6 regions most similar in terms of population, namely Bergamo, Florence, Bologna, Padua, Caserta, and Venice, are shown. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. Right panels provide ratios between RMSPEs after and before 2006 for each treated (placebo) unit. Genoa (darker bar) and remaining 26 placebo regions. In the *noIIT* sample all patents that refer to IIT have been identified and dropped from the analysis.

Aimed to further verify results in left panels of Figure 5 and to assess the statistical significance of paper's findings at conventional confidence levels, the RMSPE, before and after the treatment, is considered to perform a post-IIT/pre-IIT RMSPE ratios test. Indeed, although large gaps in outcomes of interest could be observed after 2006, this is not necessarily indicative of a significant impact of IIT if such differences have been relevant also before the intervention, i.e. if the SCM is unable to closely imitate outcomes paths before the treatment. Therefore, a wide post-IIT RMSPE does not represent a significant impact of IIT if the pre-IIT RMSPE is also large.

Figure 5 (right panels) shows post-IIT/pre-IIT RMSPE ratios for Genoa (darker bar) and other 26 major regions considered in the placebo analysis. Genoa clearly stands out both when considering the *Full* sample and the *noIIT* one, since its results are unusually larger than those obtained for placebo regions; in particular, by randomly picking one of the 27 largest regions from the placebo study, the probability of getting a ratio as high as this would be 1/27 = 0.037. Therefore, the impact of IIT on the regional innovative capacity is positive and statistically significant at the 5% level.

Lastly, notice that results are also robust to the exclusion of some regions from the donor-pool. In particular, Appendix B highlights that estimates are not driven by the specific innovative performance of the main donor (i.e. the region with the higher weight in Tables 3 and 6, Ferrara); moreover, results are also confirmed when dropping regions of Milan, Pisa, Turin and Rome from the donor-pool, out of possible concerns that the presence of secondary IIT scientific laboratories in the latter might bias estimates.[42]

4.2. Impact on Other Outcomes.

In this Section the paper investigates whether the creation of IIT in 2006 may have influenced other economic outcomes, i.e. the endowment of highly

[42]It is worth noting that, despite IIT's central laboratories are located in Genoa, other regions host secondary labs, an issue that raises concerns about the possibility of similar (albeit scaled-down) effects in the latter. In order to address this concern, the SCM is replicated on the regions of Milan and Rome, the two largest ones other than Genoa in terms of research competences (see Figure A.2). Appendix B provides results from this exercise, excluding a causal impact of IIT's secondary labs on any measure of outcome considered for such regions.

specialised human-capital in research and knowledge base (proxied by the number of local inventors per-capita) or per-capita GDP.

Some preliminary evidence is first provided by implementing a DiD model, as Table 8 shows.[43] In particular, research competences are first analysed (columns from 1 to 4) and then, in columns (5) and (6), the analysis is replicated to assess the impact of IIT on per-capita GDP.

Table 8: Impact of IIT on Research Competences and GDP. DiD Estimates.

Dependent Variable:	*Inventors per-capita*				*GDP per-capita*	
	(1)	(2)	(3)	(4)	(5)	(6)
$Genoa * Post_{2006}$	0.370***	0.366***	0.275***	0.270***	0.090***	0.092***
	(0.042)	(0.043)	(0.042)	(0.042)	(0.009)	(0.009)
Region FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Sample	*Full*	*Full*	*noIIT*	*noIIT*	*Full*	*Full*
IIT Secondary Labs	✓	✗	✓	✗	✓	✗
Observations	3,420	3,276	3,420	3,276	3,420	3,276
Adjusted R-squared	0.884	0.879	0.884	0.879	0.959	0.957
F Test (p-value)	0	0	0	0	0	0

Notes: Results of the estimation of a DiD model. Estimates in columns from (1) to (4) rely on the per-capita number of inventors residing in the region as dependent variable, while those in columns (5) and (6) rely on per-capita GDP. The variable of interest is the interaction term between the dummy variable for Genoa and that for years after 2006. The specification includes region and year fixed effects. The *noIIT* sample does not include inventors belonging to IIT. Regressions in even columns do not include observations from regions that host main IIT secondary labs (Milan, Pisa, Turin and Rome). A one has been added to the inventor count variable before taking the log to include observations with values of zero. Standard errors clustered at Nuts-3 regional level in parenthesis *** p<0.01, ** p<0.05, * p<0.1

Results in columns (1) and (2) of Table 8 indicate that the implementation of IIT has triggered a rise in the endowment of highly specialised human-capital (about 44.78%). Moreover, when considering the *noIIT* sample, a 31.65%

[43]DiD models are built like in Section 4.1. Standard errors are clustered at Nuts-3 regional level. The *noIIT* sample does not include inventors belonging to IIT, while the specification in even columns does not include regions that host main IIT secondary labs (Milan, Pisa, Turin and Rome).

increase in the number of inventors residing in the treated region (and not directly linked to IIT) is detected, thus suggesting important human-capital agglomeration. Finally, estimated effects in columns (5) and (6) suggest a significant positive impact also on regional economic performances (9.42%).

As usual, concerns about DiD models are addressed by relying on the SCM. In the top panel of Figure 6 results for research competences are shown, while the ones for per-capita GDP are depicted in the bottom panel. Region weights and predictors balance are reported in Table 9. Finally, Table 10 contains detailed results.

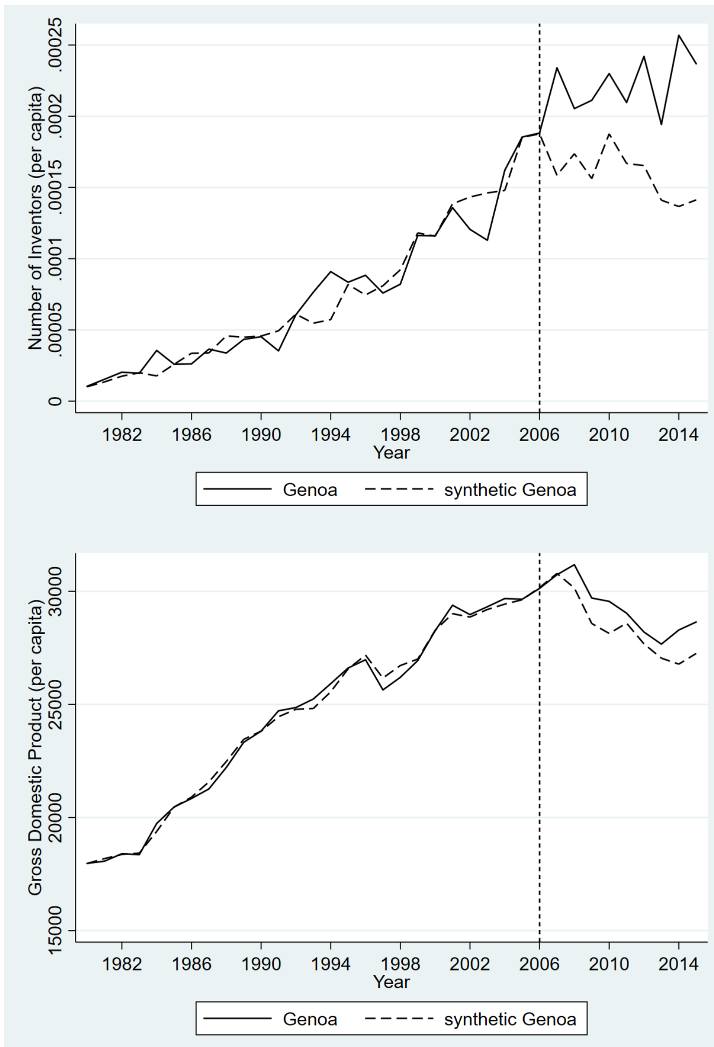
Table 9: Impact of IIT on Research Competences and GDP. Predictors Balance and Region Weights.

Region	Weight	Predictors Balance	Treated	Synthetic
Bologna	.028	Inventors (million inhabitants 1980-2006 mean)	75.70	75.70
L'Aquila	.255	Inventors (million inhabitants 1980)	10.40	10.10
Livorno	.273	Inventors (million inhabitants 1985)	25.90	25.90
Naples	.179	Inventors (million inhabitants 1990)	45.20	45.70
Rome	.065	Inventors (million inhabitants 1995)	83.50	81.90
Savona	.017	Inventors (million inhabitants 2000)	116.00	115.80
Siena	.072	Inventors (million inhabitants 2005)	185.40	185.20
Varese	.111	Researchers (1980-2006 mean)	584.56	538.18
Region	Weight	Predictors Balance	Treated	Synthetic
Alessandria	.037	GDP (per capita 1980-2006 mean)	24,554.15	24,550.20
Belluno	.052	GDP (per-capita 1980)	17,971.91	17,968.48
Catanzaro	.054	GDP (per-capita 1985)	20,464.66	20,459.81
Forlì-Cesena	.152	GDP (per-capita 1990)	23,819.68	23,818.01
Pescara	.276	GDP (per-capita 1995)	26,610.72	26,574.63
Savona	.371	GDP (per-capita 2000)	28,258.93	28,275.95
Trieste	.058	GDP (per-capita 2005)	29,650.52	29,629.69

Notes: Predictors balance and region weights (*Full* sample) for specifications that analyse research competences (top panel) and per-capita GDP (bottom panel). The SCM assigns critical weights in order to built a synthetic control that minimize the distance from the treated region in terms of research competences and predictors of its subsequent growth. Such predictors are chosen in order to minimize the RMSPE. A one has been added to the inventor count variable before taking the log to include observations with values of zero.

Referring to research competences, as shown in Figure 6, the synthetic Genoa closely matches the real one in almost all pre-intervention period, being very similar in terms of pre-intervention values of outcome predictors. In particular, for Genoa an increase in the number of inventors is clearly

Figure 6: Impact of IIT on Research Competences and GDP. Trends for Genoa and Synthetic Control.



Notes: Research competences (Inventors per-capita, top panel) and GDP per-capita (bottom panel) of the treated region (Genoa) and its synthetic counterfactual (*Full* sample). The weights used to build the synthetic control and predictors balance are reported in Table 9. A one has been added to the inventor count variable before taking the log to include observations with values of zero.

Table 10: Impact of IIT on Research Competences and GDP. SCM Effect Estimates.

Year	Inventors - Treated (million inhabitants)	Inventors - Synthetic (million inhabitants)	Absolute Difference	Relative Difference
2007	234.05	158.56	75.49	38.46%
2008	205.37	173.70	31.67	16.71%
2009	211.18	156.23	54.95	29.91%
2010	229.95	187.67	42.28	20.25%
2011	209.63	166.85	42.78	22.73%
2012	242.07	165.38	76.69	37.64%
2013	194.22	141.07	53.15	31.70%
2014	256.87	136.65	120.22	61.10%
2015	236.86	141.27	95.59	50.56%
Year	GDP - Treated (per-capita)	GDP Synthetic (per-capita)	Absolute Difference	Relative Difference
2007	30,735.35	30,792.13	-56.78	-0.18%
2008	31,179.37	30,147.47	1,031.90	3.37%
2009	29,703.49	28,576.60	1,126.90	3.87%
2010	29,557.11	28,139.01	1,418.10	4.92%
2011	29,035.90	28,593.49	442.41	1.54%
2012	28,200.95	27,677.46	523.49	1.87%
2013	27,666.15	27,045.79	620.36	2.27%
2014	28,290.43	26,781.69	1,508.74	5.48%
2015	28,645.48	27,252.68	1,392.80	4.98%

Notes: Research competences (Inventors per-capita, top panel) and GDP per-capita (bottom panel) of the treated region (Genoa) and its synthetic counterfactual (*Full* sample). The weights used to build the synthetic control and the predictors balance are shown in Table 9. The absolute effect is the total difference between the treated and the synthetic control units, while the relative effect is the absolute effect divided by the mean between real outcome and synthetic control estimate. A one has been added to the inventor count variable before taking the log to include observations with values of zero.

highlighted after 2006. Indeed, the synthetic control shows about 66 fewer inventors per million inhabitants every year then the real one, with relative annual differences that range from 16.71% to 61.10% (top panel of Table 10). In addition, the number of inventors displays an increasing trend for Genoa, while this is not true for the synthetic corresponding area. These findings seem to confirm the idea that the realization of IIT in 2006 has caused an increase in human-capital in the region (34.34% per-year on average), arguably due to agglomeration processes of firms and scientists.

Turning to per-capita GDP, the synthetic control sensibly replicates the real Genoa in the whole pre-treatment period, as the bottom panel in Figure 6 confirms. If one believes in the goodness of fit among the synthetic control and Genoa during the period prior the intervention, estimates show evidence for a small but meaningful lagged impact of IIT on local GDP per-capita (3.12% per-year on average).[44]

These findings agree with the idea that public-funded research institutes are central actors in the knowledge-based economy, key drivers of innovation and major agents of economic growth.[45] Indeed, as suggested by Valero and Van Reenen (2019), public funded research can influence regional growth through a variety of channels, i.e. a greater supply of human capital, more innovation, and demand effects.

First, this Section highlights how IIT has been fundamental to develop and attract human capital and skilled workers, which are obviously more productive than unskilled ones, and the literature generally agrees that human capital is fundamental for regional development and growth (e.g. Hall and Jones, 1999; Sianesi and Van Reenen, 2003; Cohen and Soto, 2007). Moreover, as suggested by Card (2001), geographical proximity to universities and research centres as IIT seems to benefit hosting regions both from increasing the chances that local undergraduate and graduate students will have interactions with the latter institutions and also because high-skilled workers who had been trained by the same are more likely to seek work (or to develop

[44]The lag in the impact appears plausible since the implementation of IIT took some time before producing its effects on GDP.

[45]Overall results seem to be aligned to Liu (2015) and Valero and Van Reenen (2019) ones.

start-ups) in the area where research centres are located.

Second, as illustrated in Section 4.1, IIT may affect regional growth via the channel of innovation. The latter is both a direct influence, as IIT statutorily produces innovation both individually and in collaboration with companies and other institutions, and an indirect one, as it generates and attracts better human capital.[46] Moreover, it is worth noting that IIT attracts high-tech firms, high-quality researchers, PhDs and star scientists within the hosting region, and the latter are those actors that larger benefit productivity and that uniquely have positive long-lasting effects on knowledge accumulation and knowledge spillovers (Waldinger, 2016).

Third, IIT may influence regional growth through a demand channel: indeed, increased consumption from its researchers and staff as well as the IIT' purchase of local goods and services may have had actually a significant impact on per-capita GDP. Moreover, this channel is enhanced by agglomeration of new human capital and firms into the region, or when institutional costs are subsidized by policymakers from tax revenues mostly gathered outside the hosting region.[47]

Therefore, the link among GDP per-capita and public research conducted by IIT might be not merely driven by the direct expenditures of the research centre, its staff and students, but it is in fact mediated through an increased supply of highly specialised human-capital and higher innovation.[48]

[46] See Toivanen and Väänänen (2016); Andrews (2017); Watzinger et al. (2018).

[47] Valero and Van Reenen (2019) show that public-funded research growth has a strong correlation with later GDP per capita growth at the sub-national level.

[48] Notice that results may simply reflect the spatial reorganization of economic activity. However, other neighbouring regions, except Savona, are never considered in the construction of the synthetic control, strongly alleviating such potential source of bias.

4.2.1. Robustness Analysis

In order to verify previous results, an extensive robustness analysis is provided.

First, the concern that the increase in highly-skilled human-capital into the hosting region, as previously estimated, may be solely driven by the growth of IIT's scientific staff is addressed.

Indeed, as in Section 4.1.1, by applying the SCM on the *noIIT* sample, in which all inventors that refer to IIT have not been considered, one may disentangle between scientific staffs directly employed in IIT's activities and those referring to private firms and other institutions, thus allowing a better analysis of agglomeration effects.

Table 11: Impact of IIT on Research Competences. SCM Effect Estimates (*noIIT* sample).

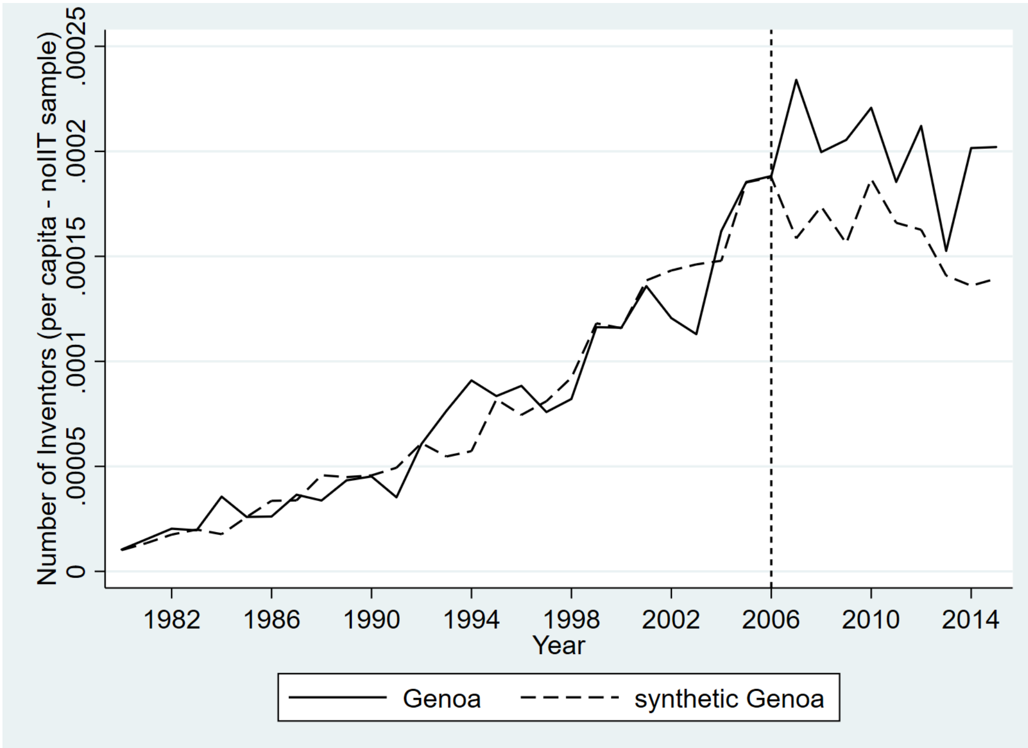
Year	Inventors - Treated (million inhabitants)	Inventors - Synthetic (million inhabitants)	Absolute Difference	Relative Difference
2007	234.05	158.56	75.49	38.46%
2008	199.63	173.70	25.93	13.89%
2009	205.45	156.23	49.22	27.22%
2010	220.76	186.87	33.89	16.63%
2011	185.44	165.99	19.45	11.07%
2012	212.10	162.64	49.46	26.40%
2013	152.60	140.84	11.76	8.02%
2014	201.58	136.01	65.57	38.85%
2015	202.03	139.37	62.66	36.71%

Notes: Research competences (Inventors per-capita) of the treated region (Genoa) and its synthetic counterfactual (*noIIT* sample). The absolute effect is the total difference between the treated and the synthetic control units, while the relative effect is the absolute effect divided by the mean between real outcome and synthetic control estimate. A one has been added to the inventor count variable before taking the log to include observations with values of zero. In the *noIIT* sample all inventors belonging to IIT have been identified and dropped from the analysis.

Figure 7 and Table 11 provide results of such exercise.[49] The analysis

[49]The weights used to build the synthetic control and predictors balance, not reported, are are available on request.

Figure 7: Impact of IIT on Research Competences. Trends for Genoa and Synthetic Control (*noIIT* sample).



Notes: Research competences (Inventors per-capita) of the treated region (Genoa) and its synthetic counterfactual (*noIIT* sample). A one has been added to the inventor count variable before taking the log to include observations with values of zero. In the *noIIT* sample all inventors belonging to IIT have been identified and dropped from the analysis. The weights used to build the synthetic control and predictors balance, not reported, are are available on request.

provides robust evidence that the intervention has caused an increase research competence; moreover, outcome patterns, though smaller in magnitude, are quite similar to those previously found, thus confirming results in the baseline specification. Specifically, the location of IIT has impacted on research competences (in the form of private firms' inventors) by about 43.71 more inventors per million inhabitants every year (24.14% higher, on average, with respect to the synthetic Genoa). Such finding arguably confirms the attraction of high-skilled workers and high-tech firms in the region, which in turn may favour agglomeration economies and networking. In particular, public-funded activities conducted by IIT may make local private firms more productive because of knowledge spillovers and agglomeration economies in the form of localized increasing returns to scale. Finally, one may also argue that an additional benefit of IIT is the creation of highly specialized human-capital that has skills valued by private firms, thus corroborating the process of knowledge production and accumulation.

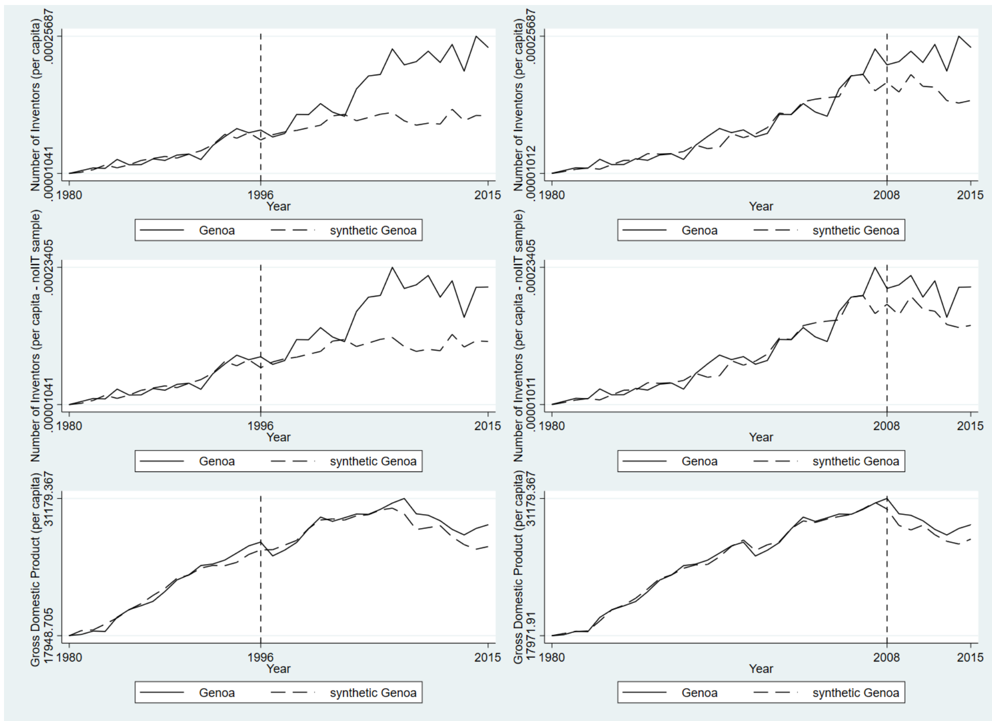
Second, as in Section 4.1.2, a variety of robustness checks are provided. In particular, usual "in-time placebos" and "in-space placebos", are proposed, as well as sensitivity checks on the exclusion of certain regions from the donor-pool.

"In-time placebos" tests are provided in Figure 8. Once again, main specifications are performed by shifting the timing of the treatment in *fake* years 1996 and 2008. The rationale is that any detected impact of the treatment in *fake* years should be suspicious as it would cast some doubts also on the effects found in previous analysis. What emerges from Figure 8 is the absence of any impact of IIT on outcomes of interest after *fake* implementation years 1996 (left panels) and 2008 (right panels), thus corroborating the validity of the research design.

Then, usual "in-space placebo" inference is performed in Figure 9.[50] Again,

[50] As in Section 4.1.2, the inference analysis for the SCM approach relies on outcome gaps between Genoa (black line) and 26 regions (those endowed of an average population above 570284 inhabitants) as placebo. For reasons of graphical representation only outcome gaps for Genoa and the 6 regions most similar in terms of population, namely Bergamo, Florence,

Figure 8: Impact of IIT on Research Competences and GDP in *Fake* Years. Trends for Genoa and Synthetic Control.



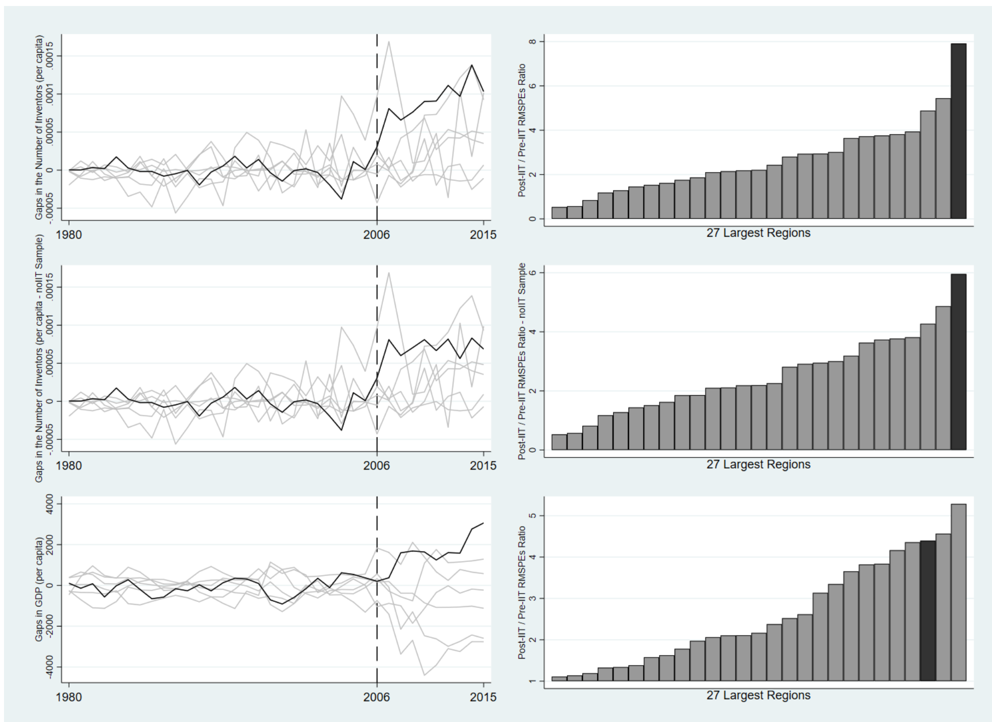
Notes: Research competences (Inventors per-capita, in top panels) and GDP per-capita (in the bottom panel) of the treated region (Genoa) and its synthetic counterfactual. *Fake* years of the treatment are assumed to be 1996 (left panels) or 2008 (right panels). A one has been added to the inventor count variable before taking the log to include observations with values of zero. In the *noIIT* sample all inventors belonging to IIT have been identified and dropped from the analysis. Effect estimates, predictors balance and weighting matrix, not reported, are available on request.

placebo permutation studies reassess the pseudo-effect of the establishment of IIT on untreated comparison regions, allowing the achievement of a distribution of the test statistic under the null hypothesis of no treatment effect against which the actual effect on Genoa can be compared. The impact of IIT on outcomes of interest will deem statistically significant if the estimated

Bologna, Padua, Caserta, and Venice, are shown. Appendix B provides detailed graphs of this inferential exercise (all 27 outcome gaps), based on which comments refer.

effect for Genoa is unusually large with respect to the distribution of placebo effects.

Figure 9: Inference. Placebo Gaps and Post-IIT/Pre-IIT RMSPEs Ratios.



Notes: Left panels provide inference analysis for the SCM approach, showing gaps between outcomes in treated (placebo) regions and corresponding synthetic ones. Genoa (black line) and 26 regions (those endowed of an average population above 570284 inhabitants) as placebo. For reasons of graphical representation only outcome gaps for Genoa and the 6 regions most similar in terms of population, namely Bergamo, Florence, Bologna, Padua, Caserta, and Venice, are shown. A one has been added to the inventor count variable before taking the log to include observations with values of zero. Right panels provide ratios between RMSPEs after and before 2006 for each treated (placebo) unit. Genoa (darker bar) and remaining 26 placebo regions. The first two panels refer to research competences (Inventors per-capita), while the bottom panel refers to GDP per-capita. In the *noIIT* sample all inventors belonging to IIT have been identified and dropped from the analysis.

First two top panels of Figure 9 show inference for research competences, while the bottom panel provides that for GDP per-capita: as usual, the solid black line is the real effect of IIT on the treated region, while grey lines are placebo gaps, which are plotted for comparison purposes. Moreover, in right panels Pre-IIT / Post-IIT RMSPEs ratios are depicted. Once again, the impact of IIT on outcomes of interest is unusually large compared to the distribution of placebo effects. In particular, Genoa clearly stands out in all left panels, also recording the highest RMSPE ratio for research competences. Since the placebo test is iterated 27 times, the probability of estimating a placebo impact as large as the true effect of IIT on Genoa's research competences under random permutation of the intervention is therefore 1/27 = 0.037, in the conventional 5% level of statistical significance. Otherwise, the estimated effect of IIT on GDP per-capita seems to be not statistically significant; indeed, the graphical evidence from the distribution of Post-IIT/Pre-IIT RMSPEs ratios in the bottom-right panel is somewhat weaker, being slightly not significant (3/27 = 0.111). However, if one considers estimated gaps in GDP per-capita, it should be noticed how the treatment impact for Genoa is unusually larger with respect to the distribution of other regions' gaps. In particular, at the end of the observational period, Genoa shows the second estimated gap over 27 tests (see Figure B.7, in Appendix B).[51] Since the chances of obtaining a ratio as high as this one would be 2/27 = 0.074, the impact of IIT on GDP per-capita in the treated region is positive and statistically significant at the 10% level.

Finally, in Appendix B usual sensitivity checks on the exclusion of certain regions from the donor-pool are proposed. In particular, results from the SCM

[51] It is worth noting that the graphical illustration in left panels of Figure 9 is restricted to only 6 regions most similar to Genoa in terms of average population, namely Bergamo, Florence, Bologna, Padua, Caserta, and Venice: in Appendix B are provided results without graphic simplifications, from which one can observe how the treatment impact for Genoa is the second highest among placebo permutation tests.

specification that does not consider regions that host main IIT secondary labs (Milan, Pisa, Turin and Rome) exclude concerns that estimates could be driven by the specific economic performance of a single region, or that the presence of IIT's secondary labs in some regions other than Genoa may have biased results.

5. Conclusions

This work adds on the innovation and regional economics literature leveraging on the institution of Italian Institute of Technology (IIT), a public-funded research centre located in Genoa since 2006, as a policy change useful to understand the causal effect of such kind of institutes on regional innovation and growth. The Synthetic Control Method (SCM) is exploited to analyse the regional innovative capacity in 1980-2015 period, using patents per-capita as a proxy. Research competences and regional economic performances, proxied by the number of local inventors and per-capita GDP respectively, are also scrutinized.

Main results suggest that IIT, on average, has led to about 22.5 more patents per million inhabitants every year. The paper then provides evidence of significant (local) knowledge spillovers from IIT to neighbouring firms. Further, Genoa shows, on average, about 66 more inventors per million inhabitants every year than the synthetic one, thus suggesting agglomeration economies. Finally, GDP per-capita is also positively affected by the location of IIT in 2006, thus suggesting the idea that the link among GDP per-capita and public research might be not merely driven by the direct expenditures of research centres, their staff and students, but it is in fact mediated through an increased supply of highly specialised human-capital and higher innovation. Notice that paper's findings are robust to a variety of placebo and sensitivity tests.

Overall results are aligned to those in Goldstein et al. (1995), Drucker and Goldstein (2007), Castelnovo and Dal Molin (2020) and Bastianin et al. (2021). Improvements in regional innovation, research competences and economic growth, induced by high quality scientific research from new research centres, are confirmed also in Cowan and Zinovyeva (2013), Kantor and Whalley (2014), Liu (2015) and Valero and Van Reenen (2019). Moreover, the idea that public-funded R&D "crowds in" rather than "crowds out" firms' innovation is also supported (Moretti et al., 2019).

Main findings might be due to several economic mechanisms, as agglomeration economies working through the attraction within the treated region of high-tech firms, high-quality researchers, PhDs and star scientists, the development of a (local) knowledge base as well as formal competences and industrial liaisons, knowledge diffusion across space, networking economies and learning processes. Moreover, IIT may have filled gaps in R&D's missing infrastructure. Finally, IIT may influence later regional growth through a demand channel and the interaction of aforementioned mechanisms.

Finally, given the broader trend of setting up PRIs across Europe, like the Institute of Science and Technology Austria (IST) or the European Institute of Innovation and Technology (EIT), these results highlight relevant policy implications related to the appropriateness and effectiveness of the allocation of public resources to such kind of innovation policies. In particular, findings may provide some potential useful insights to inform policy-makers about the marginal benefits of additional research funding against which to compare opportunity-costs in terms of taxpayer money deployed and the welfare loss attributable to taxation. Indeed, the assessment of a significant stream of private and social returns, in terms of innovation, economic growth and general agglomeration economies, from public-funded research centres is essential to justify their financing.

A possible future development could concern the possibility of conducting a comparative study of PRIs scattered across Europe. The existence of possible confounding effects that are difficult to control due to inherent regional characteristics or other contemporary innovative policies across European countries that might bias results of a SCM approach have discouraged such a development in this article. However, despite requiring a different methodological approach like a network analysis or a gravity model of ideas, a similar analysis could be relevant to refine the assessment of the impact of PRIs on regional economic performance across a broader spectrum of analysis.

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Appendix A

The Italian Institute of Technology

The Italian Institute of Technology (IIT) is a public-funded research centre based on the legislative decree 269/03, transformed into law No. 326/2003. It has been initially conceived in 2003 for initiative of the Italian Minister of Economy and it is located in the city of Genoa as a result of a politic bargaining process.[1] IIT is supported by government funds with the aim of achieving technological and economic development through qualified basic and applied research and it is managed by a foundation that follows the rules of private law, as is the case of the Max Planck Institute in Germany.[2]

The Institute has been active since October 2005 at the central headquarter of Genoa; secondary research laboratories are presents in several national and international territories: however, it is worth noting that the latter are quite smaller than the Genoa's central one.[3] The research organisation of IIT reckon on departments and laboratories that operate in many technological fields such as advanced robotics, drug discovery and development, neuroscience and brain technologies, brain and cognitive sciences, nanochemistry, nanostructures, nanophysics, pattern analysis and computer vision.[4] In addition, IIT is present in several remote centres, where scientists collaborate with researchers at the university hosting the centre, chasing conjoint

[1]See `https://www.ilsecoloxix.it/economia/2013/01/18/news/i-baroni-della-ricerca-all-assalto-dell-iit-1.32294420`.

[2]The choice of a Foundation as type of institutional government is ascribable to a consolidated legislative orientation.

[3]Research take place in Genoa Central Research Laboratories, 11 IIT technological centres across Italy and 2 IIT outstations in US.

[4]IIT also has several joint technology laboratories with companies and public institutes.

scientific aims for the Institute and the university.[5] Figure A.1 provides graphical evidence of the geographic allocation of IIT's activities.

IIT currently employs about 2000 people, of which about 80% is attributable to the scientific area, and it is characterized by an high level of internationalization.[6] In particular, about half of the researchers come from a foreign country and 42% of the staff are women. More generally, the scientific staff consists of 7% Principal Investigator, 11% staff researchers and technologists, 41% post doc, over 41% Ph.D. students and recipients of scholarships, with an average age of 36 years. Figures A.2 and A.3 show IIT human-capital endowment.[7]

Research activities follow a specific strategic plan (currently based on 2018-2023 time-period and concerning Robotics, Nanomaterials, Lifetech and Computational Sciences, namely the 4 fundamental research domains on which the activities of the Institute are concentrated): this one consists of 16 scientific purposes, divided into 4 research domains (RDs, see Figure A.4).

[5] The list includes the Centre for Space Human Robotics in collaboration with Polytechnic University of Turin; the Centre for Nano Science and Technology in partnership with Polytechnic University in Milan; the Centre for Genomic Science in collaboration with European School of Molecular Medicine in Milan; the Centre for Neuroscience and Cognitive Systems in association with Trento University, at the headquarters of Rovereto; the Centre for Nanotechnology Innovation in collaboration with Normale University in Pisa; the Centre for Micro-Biorobotics in collaboration with Sant'Anna School of Pisa, in Pontedera; the Centre for Advanced Biomaterials for Health Care in partnership with Naples Federico II University; the Centre for Biomolecular Nanotechnologies in alliance with Lecce University; the Centre for Nano Science in collaboration with Sapienza University in Rome; the Centre for Translational Neurophysiology in collaboration with University of Ferrara; the Center for Cultural Heritage Technology in association with Ca' Foscari University in Venice; the LifeTech laboratories in formal collaborative arrangement between IIT and Harvard University; the Laboratory for Computational and Statistical Learning at the Massachusetts Institute of Technology, Boston.

[6] See `https://www.iit.it/en/web/guest/about-us`.

[7] Data updated to December 2021.

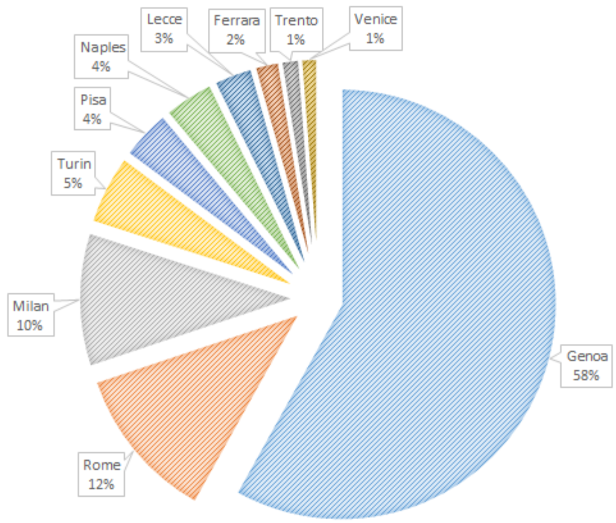
Figure A.1: Geographic Allocation of IIT's Activities.

Source: `https://www.iit.it/en/web/guest/about-us`.

I Robotics supports the developing of new hardware or software robotic platforms; in particular, there are 5 priorities, that are Mechatronics, Soft Robotics, Social Cognition and Human Robot Interaction, Biomedical Robotics and Intelligent Companion Robots.

II Nanomaterials domain focuses with new sustainable and or biodegradable materials, nano-composites, 2D materials, nano-fabrication technologies and nano-devices, and new colloid chemistry approaches. In particular, research activities affect Nanomaterials for Sustainability,

Figure A.2: IIT Human Resources Endowment for Research by Location.



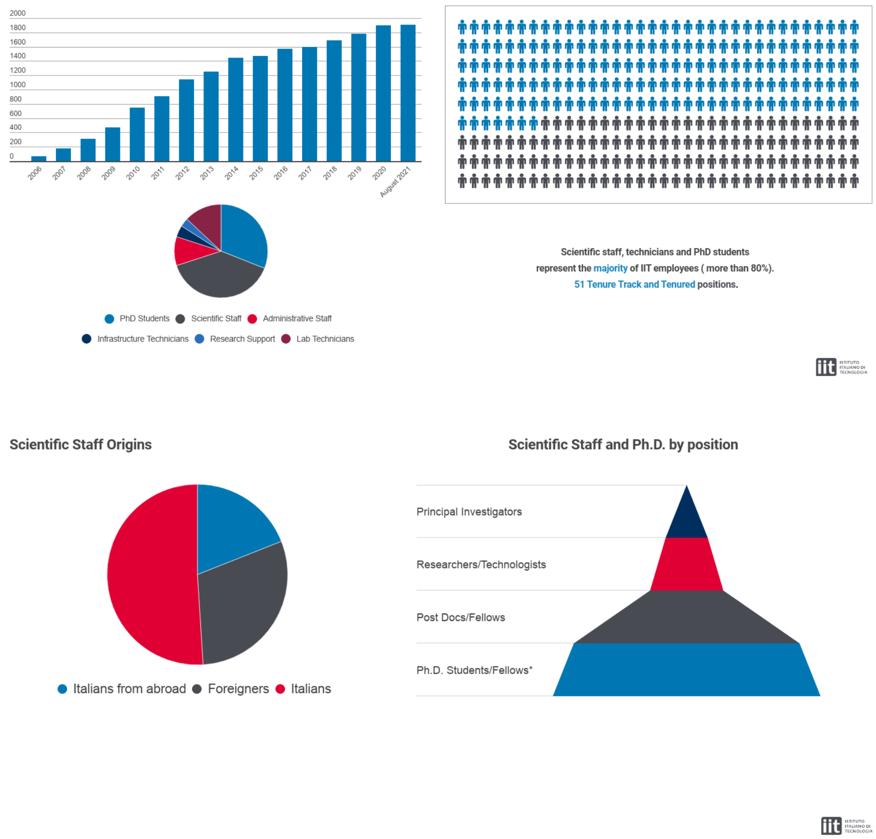
Source: Author's elaboration from `https://www.iit.it/people`.

Nanomaterials for Energy, Nanomaterials for Health and Exploratory Materials Science.

III Lifetech supports progresses in advanced electrophysiological, computational, genetic, molecular imaging and perturbation tools for dissecting the microscopic neural processes underlying brain functions. This domain is divided in 3 Priorities: Neuroscience and Brain Technologies, RNA Technologies and Technologies for Healthcare.

IV Computational Sciences tends to develop massive simulations of physical systems, repeated numerous times to generate robust statistics, and data mining of vast datasets to identify unexpected patterns. This domain will focus on 4 Priorities: Development HPC Algorithms & Software, Computational Modelling, Machine Learning, Deep Learning & AI and

Figure A.3: IIT Human Resources Endowment.



Source: Author's elaboration from https://www.iit.it/en/web/guest/about-us.

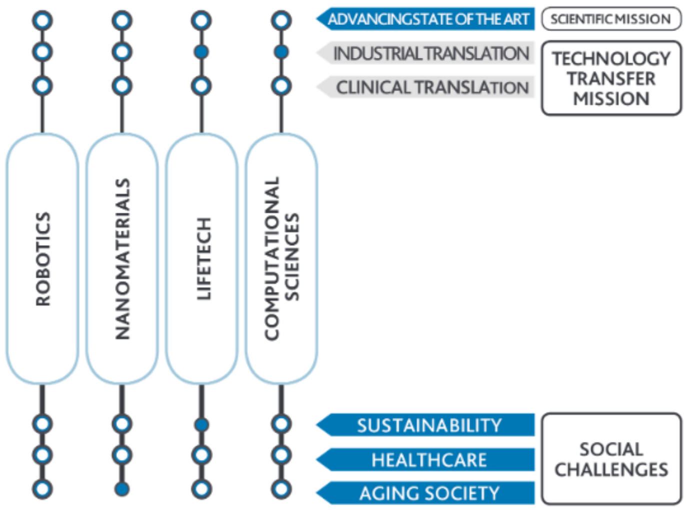
Computer Vision.[8]

Each of these Domains is developed by the Principal Investigators (PIs) and the research groups to which they refer, distributed in the Central Research Laboratories of Genoa, in the network of centers located throughout Italy and the United States.

From 2013 to 2019 IIT has attracted public funding of about €94 million

[8]Source: https://www.iit.it/research/domains.

Figure A.4: IIT Research Organization.



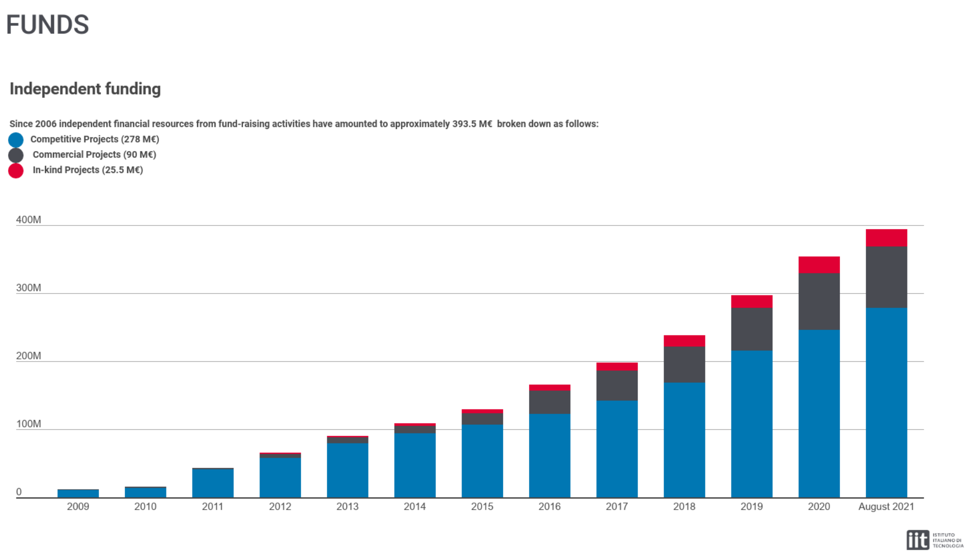
Source: https://www.iit.it/en/web/guest/about-us.

every year, 80% of which has been allocated to technical-scientific activities.[9] In addition, external funding obtained directly from the Foundation has amounted to €393 millions since 2006, of which 71% from competitive projects, 24% from commercial projects and 5% from in-kind projects (see Figure A.5).

In this context, one of the principal aims of IIT is to transfer own knowledge and technology to the society and the productive fabric with the aim to support the innovation process; moreover, IIT promotes and supports the origination of innovative start-up companies. In particular, the Institute puts in place a set of services to transfer knowledge from research to the marketplace,

[9]Source: https://www.iit.it/documents/20123/223518/Relazione+Corte+dei+Conti+2019.pdf/232831c2-4796-145f-5289-fa7594822c68?t=1622033706731

Figure A.5: IIT Independent Funding.

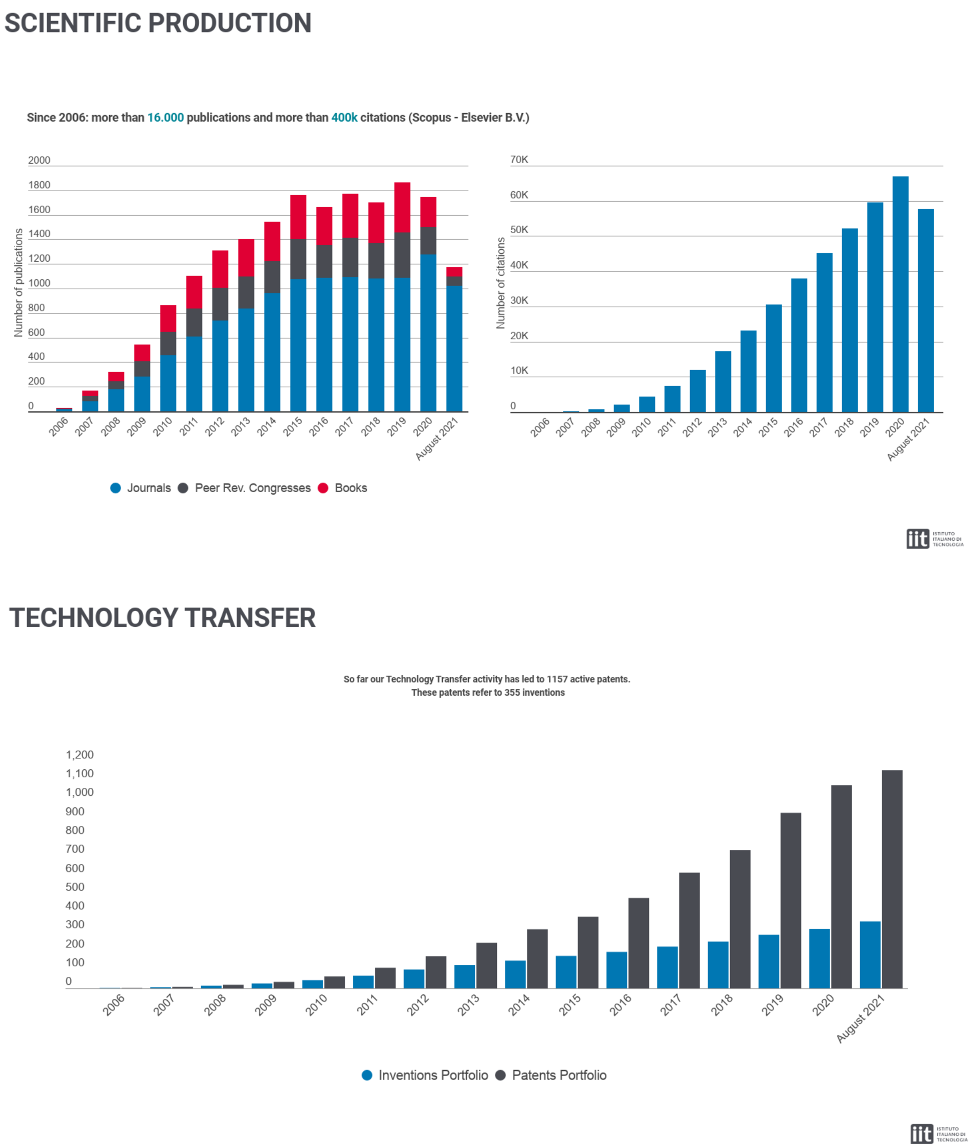


Source: `https://www.iit.it/en/web/guest/about-us`.

especially regarding the changing needs of the high-tech market: IIT activities include protection of new inventions through intellectual property rights, without forgetting the strategic licensing of IIT technological and scientific knowledge. Finally, IIT promotes the negotiation and definition of settlements with industries to realize R&D and competitive industrial research and the dissemination and training activities for the scientific community.[10] In particular, from 2006 to 2020, IIT's activities have generated a flow of approximately 16000 publications in international scientific journals and about over 200 discoveries, over 200 European projects and more than 50 ERCs, which conduct to more than 1000 active patent applications, 24 firm start-ups established and more than 40 under due diligence (see Figure A.6).

[10] Source: `https://www.iit.it/technology-transfer`.

Figure A.6: IIT Scientific Production and Technology Transfer.



Source: Author's elaboration from `https://www.iit.it/en/web/guest/about-us`.

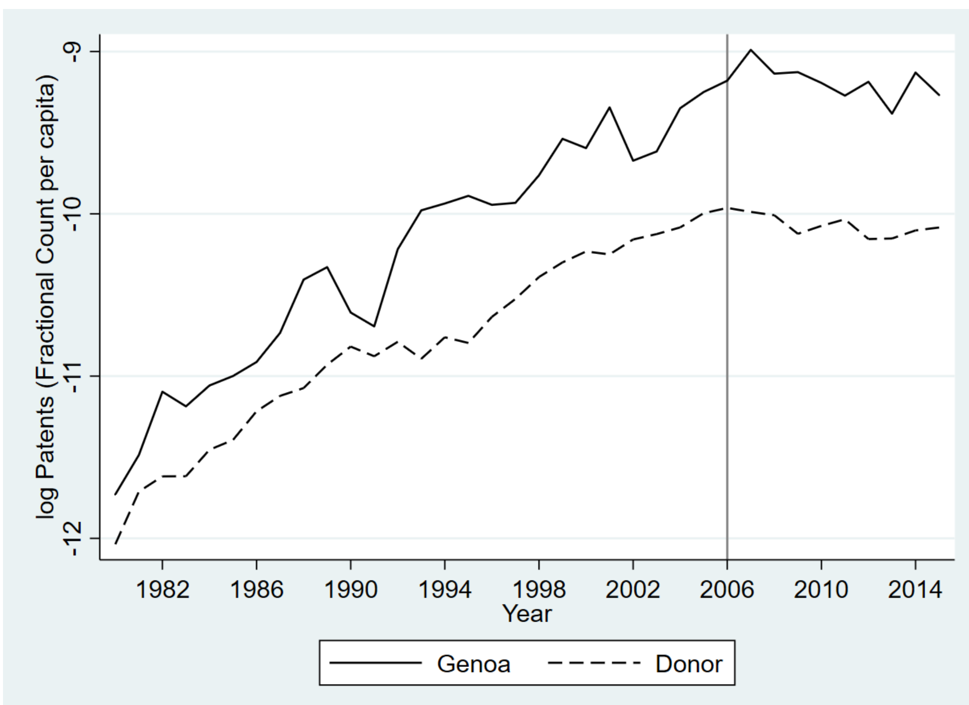
Appendix B

Additional Robustness Tests

Additional Robustness Tests for Section 4.1.2.

Although the DiD approach in Table 2 is only intended to provide simple evidence of the impact of IIT on Genoa's innovative performance, it seems useful to demonstrate the presence of pre-treatment common trends for treated and control regions. This assumption is indeed fundamental for the validity of the DiD research design.

Figure B.1: Impact of IIT on Innovation. Descriptive Evidence.



Notes: (log) Patents (fractional count) per-capita of the treated region (Genoa) and the average value of other Italian regions in the donor-pool, before and after 2006 (*Full* sample). A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero.

Simple graphical evidence is provided in Figure B.1: by relying on the *Full* sample, the innovative trend for the region of Genoa is compared to the average value of the donor-pool in the 26-year period prior to the intervention and after 2006. The two lines seem to show a parallel trend, although the innovative performance of Genoa is higher with respect to the donor-pool. Therefore, the parallel trend assumption seems to be fulfilled.

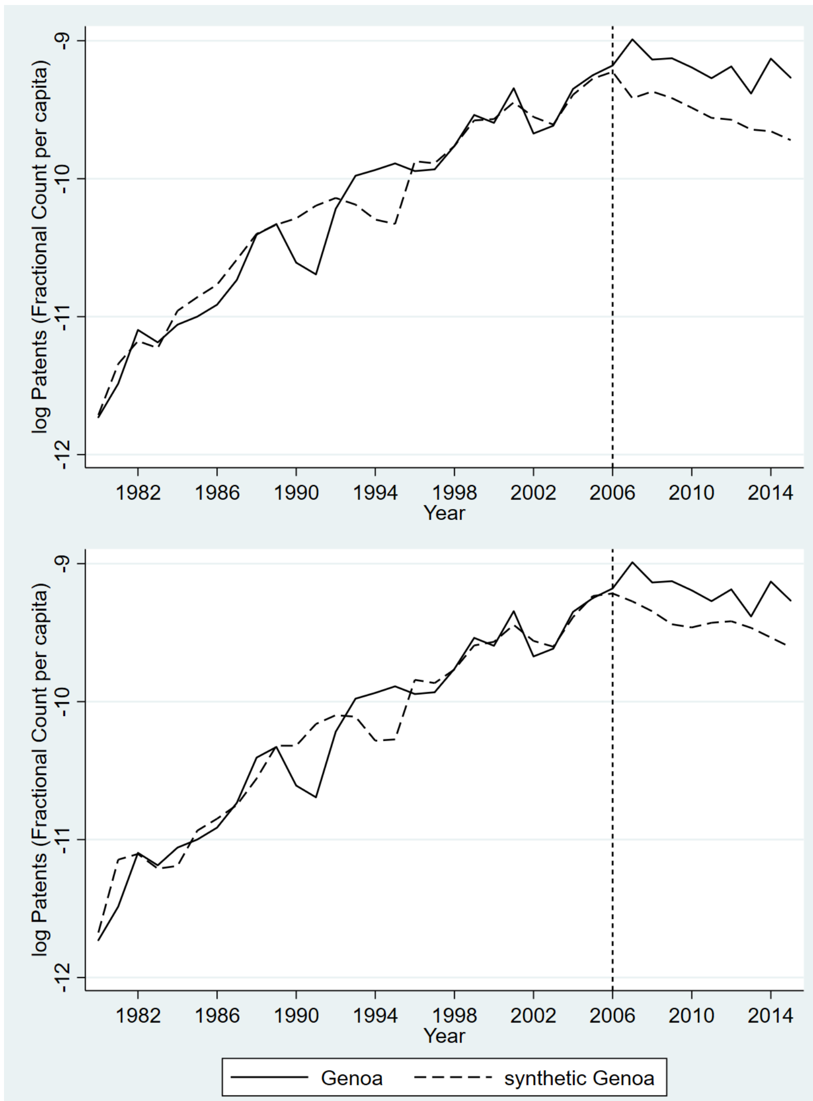
In order to further verify the validity of paper's results, a series of additional sensitivity tests are carried out. Recall from Tables 3 and 6 that the synthetic Genoa is estimated as a weighted average of 16 Italian regions. Here it is verified whether main results are sensitive to the exclusion of some donor-pool units.

First, given that the SCM only applies positive weights to certain donor-pool's units, one might argue that estimates could be driven by the specific innovative performance of a single region. By excluding the one that received the higher positive weight, even if sacrificing some goodness of fit, this initial sensitivity test allows to address such concern.

Second, given that IIT's research activity is strengthed by a wide network of laboratories all over Italy (see Appendix A), one can argue that the inclusion in the donor-pool of regions hosting branch laboratories could bias results.

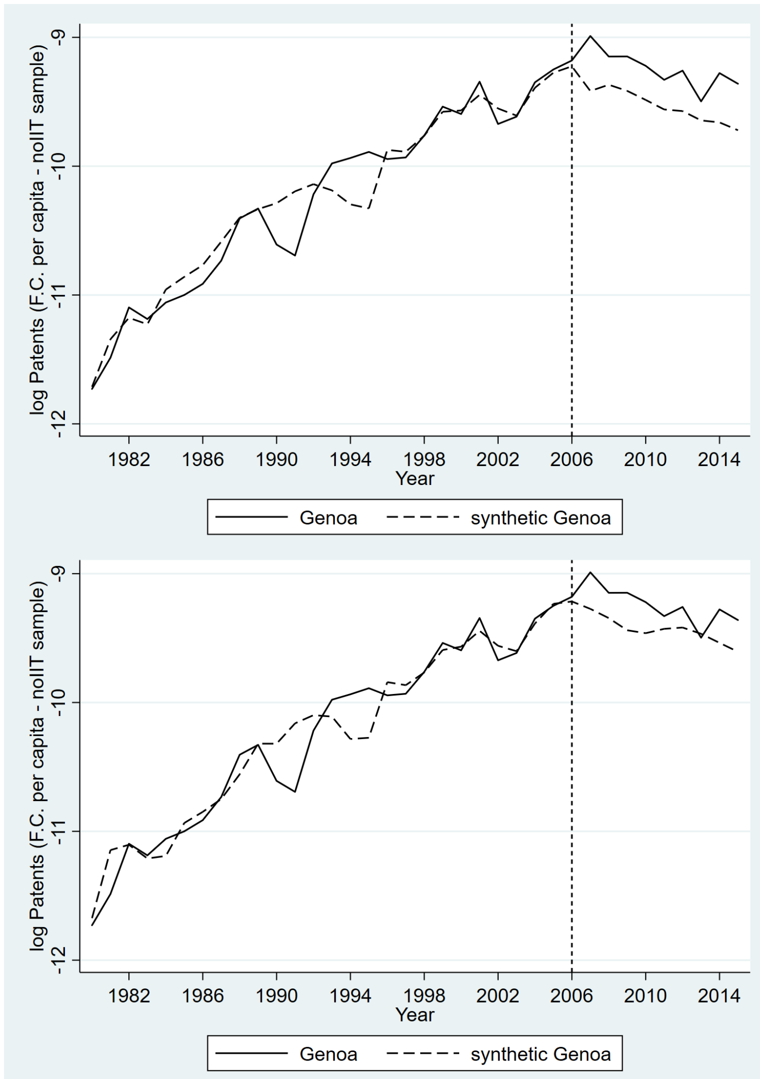
In order to address these concerns, the SCM baseline analysis is replicated on the *Full* sample (Figure B.2) as well as on the *noIIT* sample (Figure B.3), excluding from the donor-pool potentially biasing regions. Top panels of Figures B.2 and B.3 show SCM's results after excluding the region of Ferrara, that has the highest value in the weighting matrix computed by the algorithm that creates the synthetic control (see Tables 3 and 6 in Sections 4.1 and

Figure B.2: Impact of IIT on Innovation. Sensitivity of SCM Results to the Exclusion of Some Regions (*Full* sample).



Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and the synthetic Genoa (*Full* sample) built using a specification that excludes the region of Ferrara (top panel) and the regions where the major four IIT research sites are located, namely Milan, Pisa, Turin and Rome (bottom panel). A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. Effect estimates, predictors balance and weighting matrix, not reported, are available on request.

Figure B.3: Measuring Spillover Effects from IIT. Sensitivity of SCM Results to the Exclusion of Some Regions (*noIIT* sample).



Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and the synthetic Genoa (*noIIT* sample) built using a specification that excludes the region of Ferrara (top panel) and the regions where the major four IIT research sites are located, namely Milan, Pisa, Turin and Rome (bottom panel). A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. In the *noIIT* sample all patents referring to IIT have been identified and dropped from the analysis. Effect estimates, predictors balance and weighting matrix, not reported, are available on request.

4.1.1 respectively).[11] Bottom panels (Figures B.2 and B.3) provide instead SCM's results after dropping the regions of Milan, Pisa, Turin and Rome from the donor-pool, out of possible concerns that the presence of secondary IIT scientific laboratories in such regions might bias estimates.[12]
Rather comfortingly, innovative patterns shown in Figures B.2 and B.3 are quite similar to those in the baseline specification, thus alleviating concerns about these potential sources of bias. After 2006 a significant positive effect is therefore observed, suggesting the absence of different dynamic patterns between Genoa and its synthetic counterpart.

Additional Robustness Tests for Section 4.2.1.

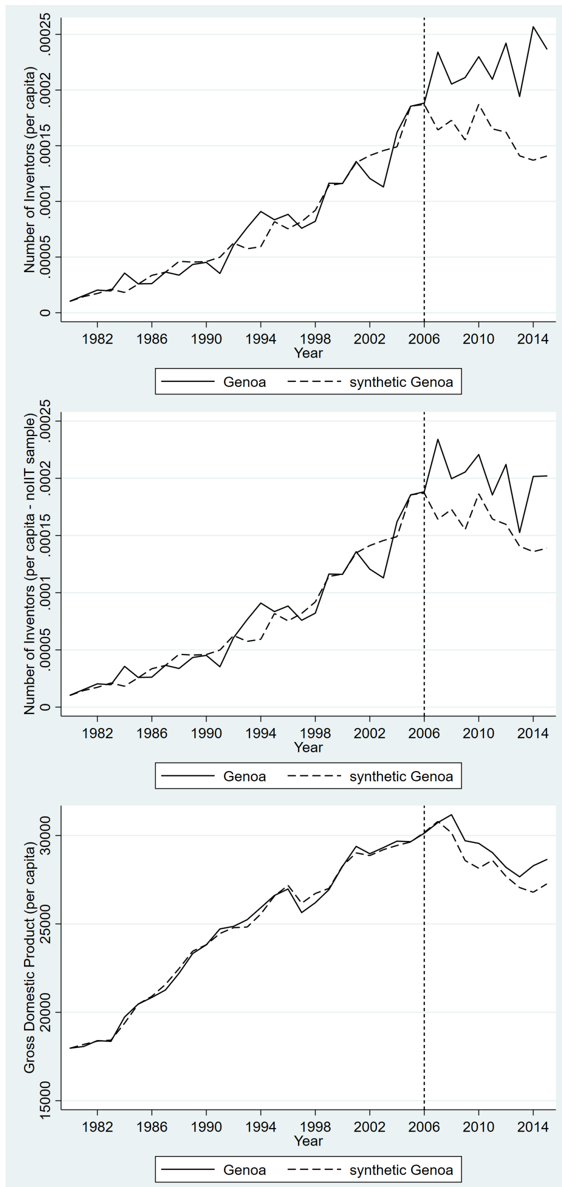
In this Section additional robustness tests for the impact of IIT on other outcomes, i.e. research competences and per-capita GDP, is provided. In particular, usual sensitivity checks on the exclusion of certain regions from the donor-pool are proposed.
Figure B.4 provides results from the SCM specification that does not consider regions that host main IIT secondary labs (Milan, Pisa, Turin and Rome). Indeed, the SCM only applies positive weights to certain donor-pool's units, and one might argue that estimates could be driven by the specific economic performance of a single region.[13]
Results from the treated region (Genoa) and its synthetic counterfactual for

[11] Predictors balance and region weights, not reported, are available on request.

[12] In particular, the regions where the four major IIT research sites, measured in terms of human resources, are excluded (see Figure A.2 in Appendix A for details). Predictors balance and region weights, not reported, are available on request.

[13] Effect estimates, predictors balance and weighting matrix, not reported, are available on request.

Figure B.4: Impact of IIT on Research Competences and GDP. Sensitivity of SCM Results to the Exclusion of Some Regions.



Notes: Research competences (inventors per-capita, in top panels) and GDP per-capita (in the bottom panel) of the treated region (Genoa) and its synthetic counterfactual. Synthetic Genoa built using a specification that excludes regions where the major four IIT research sites are located, namely Milan, Pisa, Turin and Rome. In the *noIIT* sample all inventors belonging to IIT have been identified and dropped from the analysis. A one has been added to the inventor count variable before taking the log to include observations with values of zero. Effect estimates, predictors balance and weighting matrix, not reported, are available on request.

research competences (inventors per-capita) are provided in top panels, while those for GDP per-capita are shown in the bottom one. Again, reassuringly, outcome patterns are qualitatively and quantitatively similar to those in baseline specifications, thus alleviating the aforementioned concern.

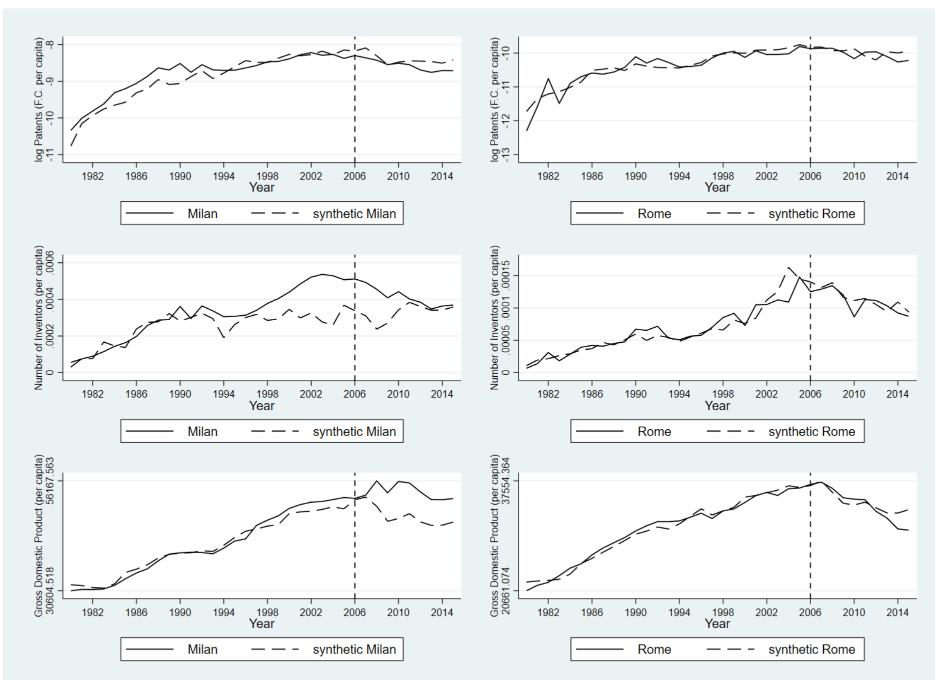
The Impact of IIT's Secondary Labs.

One main identification concern addressed in this Appendix relates to the geographic allocation of IIT's laboratories across Italy. Indeed, despite IIT's headquarter and central laboratories are located in Genoa, other regions host secondary labs, an issue that raises concerns about the possibility of similar (albeit scaled-down) effects in the latter, that may bias results.

This concern is already alleviated by the preceding analysis, which goes on to rule out possible biasing effects and confirming the identification strategy. However, in order to further analyze this issue, the SCM is replicated on the regions of Milan and Rome, the two largest regions other than Genoa in terms of research competences (see Figure A.2).

Figure B.5 contains results from this exercise. In top panels are shown results for the innovative capacity, in middle ones those for human capital and research competences, while in bottom panels SCM estimates for per capita GDP are finally provided. It is worth noting that no direct effects of IIT's secondary labs are detected on innovative performance and research competence endowment of hosting regions. Conversely, the impact of the treatment on per capita GDP, for the region of Milan, appears moderately significant (while no impact is detected for Rome). However, one should refrain to consider such result as a causal impact, given the very low dimension of Milan's IIT labs: moreover, usual SCM "in-space" inference (placebo gaps and post-IIT/pre-IIT RMSPEs ratios, not reported) casts significant doubts about such result, suggesting the presence of possible confounding factors.

Figure B.5: Impact of IIT on Innovation, Research Competences and GDP in Milan and Rome Regions.

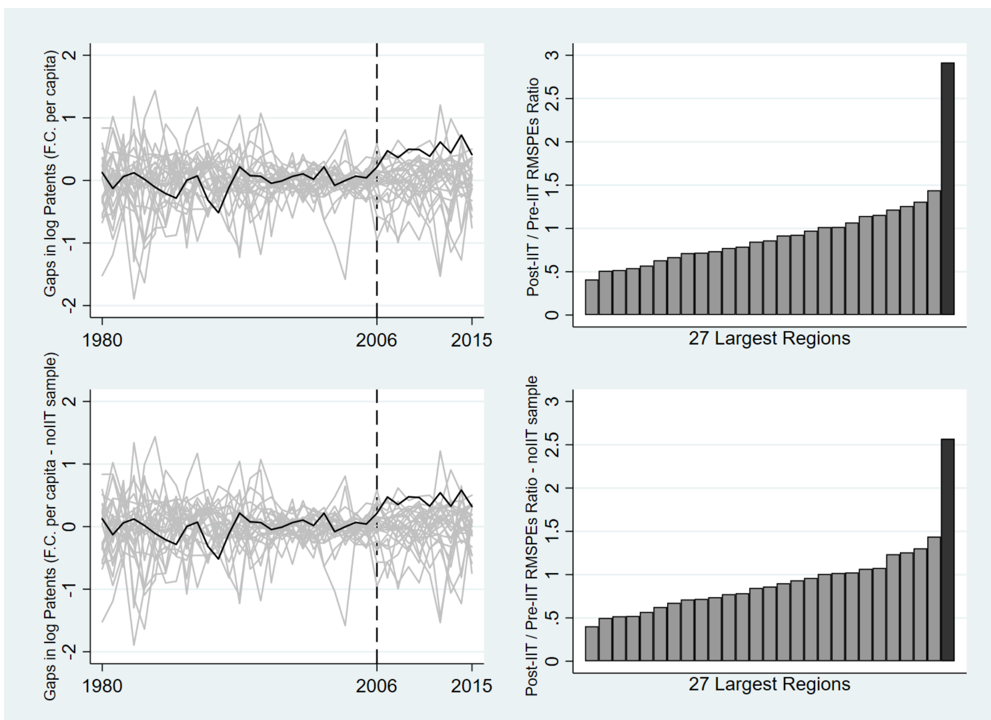


Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita (top panels), research competences (inventors per-capita, in middle panels) and GDP per-capita (in bottom panels) of regions hosting secondary IIT's labs (Milan and Rome) and their synthetic counterfactual. A one has been added to the inventor count variable before taking the log to include observations with values of zero. Effect estimates, predictors balance and weighting matrix, not reported, are available on request.

Detailed Results for Inference

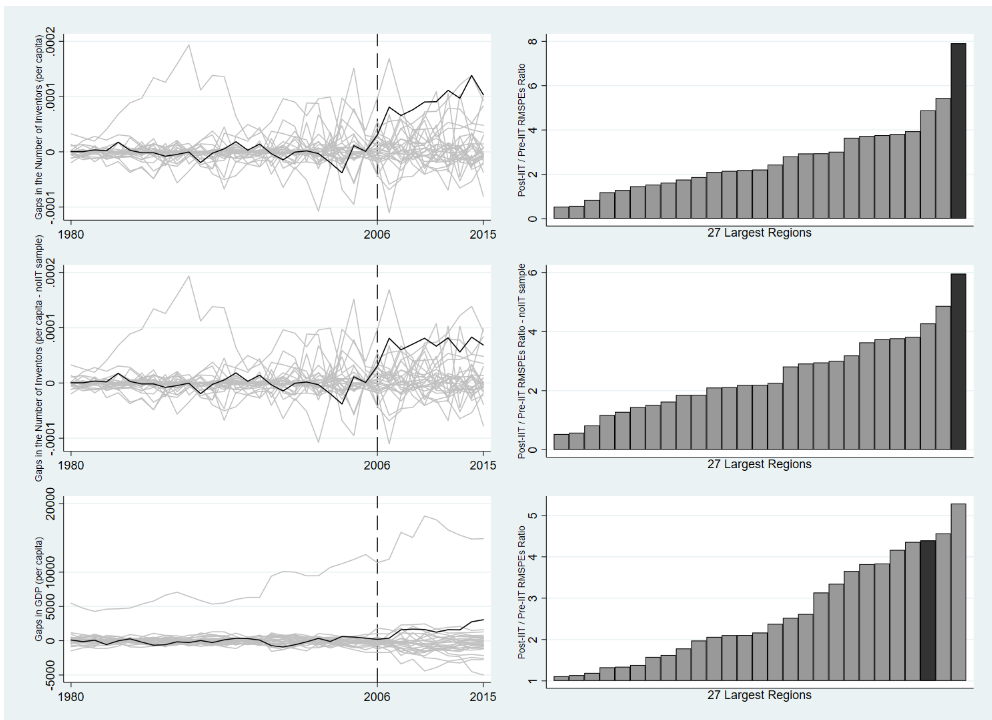
In this Appendix detailed results for inference exercises are provided: in particular, gaps between outcomes for Genoa (black line) and all 26 regions (those endowed of an average population above 570284 inhabitants) as placebo are shown. Indeed, it is worth noting that, despite being designed in the same way, in the main text, for reasons of graphical representation, only results for Genoa and the 6 regions most similar in terms of population, namely Bergamo, Florence, Bologna, Padua, Caserta, and Venice, are shown.

Figure B.6: Inference. Placebo Gaps and Post-IIT/Pre-IIT RMSPEs Ratios.



Notes: Left panels provide inference analysis for the SCM approach, showing gaps between outcomes in treated (placebo) regions and corresponding synthetic ones. Genoa (black line) and 26 regions (those endowed of an average population above 570284 inhabitants) as placebo. Right panels provide ratios between RMSPEs after and before 2006 for each treated (placebo) unit. Genoa (darker bar) and remaining 26 placebo regions. In the *noIIT* sample all patents that refer to IIT have been identified and dropped from the analysis.

Figure B.7: Inference. Placebo Gaps and Post-IIT/Pre-IIT RMSPEs Ratios.



Notes: Left panels provide inference analysis for the SCM approach, showing gaps between outcomes in treated (placebo) regions and corresponding synthetic ones. Genoa (black line) and 26 regions (those endowed of an average population above 570284 inhabitants) as placebo. Right panels provide ratios between RMSPEs after and before 2006 for each treated (placebo) unit. Genoa (darker bar) and remaining 26 placebo regions. The first two panels refer to research competences (Inventors per-capita), while the bottom panel refers to GDP per-capita. In the *noIIT* sample all inventors belonging to IIT have been identified and dropped from the analysis.

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Declaration of Competing Interest

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