The innovative impact of public research institutes: evidence from Italy

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Abstract

This paper empirically analyzes whether a prominent place-based innovation policy, the institution of the Italian Institute of Technology (IIT), has affected the treated region innovative capacity. By relying on the Synthetic Control Method (SCM) approach and Italian NUTS-3 regional panel data, the innovative development of the latter, proxied by (per-capita) fractional count of patents, is compared with a set of Italian NUTS-3 control ones. Results suggest that the establishment of IIT has impacted on the regional innovative output, on average, by about 22.5 more patents for million inhabitants per year in the post-intervention period. The paper also provides evidence of knowledge spillovers from IIT in the hosting region. In addition, positive effects on the regional endowment of high-skilled human capital as well as regional growth are also documented. 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. Finally, the paper may provide useful insights to inform policy makers about the marginal benefits of additional research funding by highlighting the stream of private and social returns, against which the opportunity cost of the intervention must be compared.

Keywords. Public Research Institutes; Regional Development; Growth; Innovation; Human Capital; Knowledge Spillovers; Knowledge Accumulation; Synthetic Control Method.

JEL Classification. I23; I25; J24; O10; O15; O18; O30; O31; R10; R11; R58.

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1 Introduction

Economists and policy makers are well aware that each country is characterised by large and persistent differences in regional economic performances; they often face such challenging issue with place-based policies addressed to foster innovation, that is essential for national and regional competitiveness (Neumark & Simpson 2015).[1]
Indeed, the role of innovation in supporting regional growth and social welfare has been extensively studied in the economics and regional science literature. As documented by seminal works from Romer (1990), Aghion & Howitt (1990) and Grossman & Helpman (1993), the expansion and the diffusion of the knowledge base is fundamental for a long-term growth in production and wealth. In addition, it is well known that incentives for private R&D investments are lower than the social optimum, due to knowledge spillovers, low appropriability of R&D and constrains in financing R&D projects caused by information asymmetries in financial markets (Harhoff 2000). Therefore, government programs to support regional innovation at socially optimal levels may be warranted.

Among different modalities in which place-based innovation policies can be formalised, some policy makers have tried to support deprived areas by means the establishment of new universities and research institutes. Indeed, as widely recognised in the economic literature, innovation is primarily affected by new knowledge (Audretsch & Feldman 1996) and universities or public research institutes are traditionally emangmed players involved in its generation and transmission.[2]
The latter are extensively believed to foster economic growth, productivity and regional innovation through a causal chain of effects between academic investments, the creation of a (local) knowledge base, knowledge spillovers and economic agglomeration (Adams 1990, Mansfield & Lee 1996).[3] In particular, Goldstein et al. (1995) and Drucker & Goldstein (2007) identify a variety of mechanisms through which modern research institutes may potentially influence the regional economic development: specifically, authors refer to the creation of knowledge and human capital, the relocation of existing know-how, the support to technological innovation, the potential increase in capital investment, the development of a regional leadership, the raise in knowledge infrastructure production and, finally, the influence on the regional "milieu".
Hence, it becomes crucial to understand if public funded research institutes, among other possible policy tools, are able to stimulate regional innovation and growth. However, with the notable exceptions of Cowan & Zinovyeva (2013), Liu (2015), Valero & Van Reenen (2019) and Moretti et al. (2019), who have found evidence in favour of agglomeration economies, local spillovers and rises in regional growth and productivity due to the influence of public research institutes, this issue has been substantially neglected by previous literature. Moreover, Bonander et al. (2016) provide some conflicting results, finding no effects of research universities on local economic performances, except for the number of PhDs and professorships. Therefore, empirical analyses relying on credible techniques for causal inference become particularly relevant in order to understand the impact of public research institutions on regional economic performances.

This study adds to the above-mentioned literature by investigating the impact of a prominent

[1]Place-based innovation policies support the development of knowledge base and new technologies by affecting the geographical distribution of high-skilled human capital, economic activities and stimulating private sectors' investments. Among other possible policy tools, they are becoming increasingly important for any government intervention addressing the generation of competitive advantages and supporting lagging regions through an innovation-driven economic transformation. See Neumark & Simpson (2015) and Duranton et al. (2015).

[2]"Silicon Valley" and "Route 128" owe their success as primary economic hubs to their closeness to Stanford and MIT (Jaffe 1989, Carlino et al. 2012).

[3]Growth theory supports the view for which the non-rivalrous nature of new knowledge explains growth in income per-capita and the presence of increasing returns to scale (Aghion & Howitt 2005, Jones 2005).

place-based innovation policy, the creation of Istituto Italiano di Tecnologia (IIT), on the innovative performance of the Italian NUTS-3 region of Genoa.[4] Established by law in 2003 (Legislative Decree 269/03, converted by Law 326/2003) and active in Genoa since October 2005, IIT is a public funded research institute, whose aim is to conduct scientific research for the purpose of technological development. In particular, IIT has spurred a huge amount of public and private investments addressed to basic and applied research, also promoting a variety of technology transfer to the market as well as knowledge sharing activities, all of which arguably favours knowledge accumulation and spillover effects. Moreover, it is worth arguing how the establishment of IIT in Genoa has been the result of a political bargaining process, thus representing a probably exogenous policy change that can be useful to understand the effect of public research centres on regional economies.[5]

A fundamental aspect in empirical analysis of publicly funded research institutes is the identification of an appropriate strategy to detect their innovative impact.[6] In particular, a challenging task is the choice of a rigorous method to identify a reliable control group. Indeed, in the absence of the latter, the identification of the effect of interest may be 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.[7] The study addresses these concerns by relying on the Synthetic Control Method (SCM) approach and Italian NUTS-3 regional panel data in order to evaluate whether public funded research institutions tend to foster knowledge creation and diffusion within the region, which in turn may favour agglomeration economies, the innovative activity and regional growth.

The SCM combines elements from Difference-in-Differences (DiD) models and matching techniques, preserving their advantages and overcoming some problems. Indeed, Propensity Score Matching (PSM) is a suitable approach to refine the control group, but it is infeasible in the presence of only one treated unit, while a DiD framework does not perform very well when policy changes are applied to a small number of treated units. In such cases, classical inference based on standard large-sample approximations may be misleading (Conley & Taber 2011). Moreover, unlike a DiD, the SCM is capable of accounting for the effect of possible confounders changing over time, by weighting the control group to better match the treatment group before the intervention (Kreif et al. 2016).

Therefore, under certain assumptions that must be fulfilled, the SCM builds a synthetic control region, the so-called “synthetic Genoa”, allowing the achievement of a proper counterfactual for the treated region and an increase in the quality of impact estimation (Abadie & Gardeazabal 2003, Abadie et al. 2010, 2015). In particular, the “synthetic Genoa” captures the development of the real one in the pre-treatment period relying on a weighted average of the outcome variable (and predictor variables) of control regions; moreover, such synthetic control not only follows the same pre-treatment trend as the treated unit, but even overlaps the same one, thus replicating the outcome path that Genoa would have experienced in the absence of the treatment. Hence, the estimated divergence in outcome trajectories for Genoa and the synthetic one can be interpreted as the causal impact of the treatment.

The main result is that the establishment of IIT has a positive and significant impact on regional innovation. Conditioning on a set of predictor variables that should affect outcomes in regions both

[4] In this work the terms "region" and "NUTS-3 region" will be used interchangeably to indicate the Italian NUTS-3 statistical territorial unit.

[5] See https://www.iit.it/it/istituto/iit and https://www.repubblica.it/rubriche/la-scuola-siamo-noi/2016/02/29/news/la_fragilita_dell_iit_l_istituto_privato_che_comandera_la_ricerca_italiana-134509491/.

[6] Since these interventions are usually very expensive and difficult to appraise and evaluate, due to their direct and indirect quantity effects, it is essential to analyse the impact of the policy related to a “no-intervention” alternative, and to evaluate the social value of the latter.

[7] It should also be taken into account the presence of possible unobservable characteristics that affect both the location of public research institutes and potential increases in local innovative and economic performances.

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% higher with respect the synthetic Genoa). 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: in particular, Genoa shows about 66 more inventors per million inhabitants every year than the synthetic one, with a relative average annual difference of 34%. Finally, evidence for a positive effect of the establishment of IIT on per-capita GDP is also found.

The SCM approach also shows some limits. Main concerns are related to the possible existence, contemporaneously to the time-period under investigation, of some confounding factors that may affect variables of interest, making the estimated impact of IIT biased. Comfortingly, other important place-based innovation policies that might blur the effect of IIT did not occur in Genoa.
Second, another concern arises from the fact that, for SCM estimators, asymptotic inference cannot be performed.[8] Therefore, to address such issue, "in-space placebos" and "in-time placebos" tests are proposed to assess the robustness of previous results. Indeed, the level of confidence about the validity of paper's results 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 (Heckman & Hotz 1989, Abadie et al. 2015). Comfortingly, paper's findings are robust to aforementioned placebo studies.
Finally, the SCM only applies positive weights to certain donor pool's units, and one might argue that estimates could be driven by the specific innovative performance of a single region. Results from sensitivity checks suggest that this is not the case and confirm all previous findings.

Main findings might be due to several economic mechanisms. One may refers to agglomeration economies working through the attraction within the treated region of high-tech firms, high-quality researchers, PhDs and star scientists, those 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, as in Liu (2015), who finds evidence in favour of direct spillovers from public research and further agglomeration economies; knowledge and technology market transfer, which contributes to the regional innovative process; knowledge sharing and specific training activities for scientific and research communities, as well as the networking with other research institutions, which arguably improve knowledge dissemination, learning processes and effectiveness in transferring technologies; filling gaps in missing R&D infrastructure. All of these mechanisms provide positive feedbacks in regional innovation dynamics: therefore the opening of a public research centre in an innovation-poor region may be an effective tool for the development policy for that one.

The study contributes to the existing empirical literature on the innovative impact of public funded research centres in a number of ways. First, while there exist studies on the economic impact of academic research, quantitative assessments of the economic and innovative effects of non-academic public research institutions are quite rare. Second, the paper is the first that analyzes the impact of such kind of place-based innovation policies using Italian regional data and a refined method to choose a reliable control group. Indeed, to the best of knowledge, empirical evidence for Italian regions is only provided by Cowan & Zinovyeva (2013), whose study, however, is based on a classic first-difference estimator and more aggregated NUTS-2 data. Further, empirical evidence on this issue, inferred from dependable techniques for causal inference, has never been provided other than for US, Sweden or once again with more aggregated data, as in Moretti et al. (2019). Third, this study applies a novel

[8]See Section 4.2.

identification strategy, the SCM matching estimator, believing that such approach is the most reliable one to assess the impact of economic shocks that are related to a specific region, while accounting for endogenous selection into the treatment. Finally, following arguments in Drucker & 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 regional milieu. Moreover, the paper suggests significant local spillovers from public research centres and confirms results in Cowan & Zinovyeva (2013), Kantor & Whalley (2014), Liu (2015), Valero & Van Reenen (2019) and Moretti et al. (2019).[9]

These results highlight relevant policy implications related to the appropriateness and effectiveness of the allocation of public resources to such kind of place-based innovation policies, providing some potential useful insights to inform policy makers about the marginal benefits of additional research funding. 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. In particular, IIT is effective at raising regional innovation and economic performances, favouring local knowledge spillovers and generating higher productivity, thus providing policy makers useful evidence against which to compare the opportunity cost in terms of taxpayer money deployed and the welfare loss attributable to taxation.

The rest of the work is structured as follows. Section 2 describes related literature while Section 3 provides detailed information about the Italian Institute of Technology. Section 4 explains the identification strategy and provides summary statistics. Empirical results are presented in Section 5, including robustness checks and placebo tests. Section 6 concludes.

2 Related Literature

This study is related to different strands of literature. First, it fits to the wide literature related to the issue of promoting regional innovation; within this context, from the seminal work of Jaffe et al. (1993), knowledge accumulation tends to be considered geographically localised. This generates knowledge spillovers and positive technological externalities that affect the location of firms and high-skilled human capital, thus inducing a dynamic process that fosters growth.[10]

Innovation is then supported by a variety of 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. It is worth noticed that innovation is also fostered by local inter-firm alliances, mutual information and interactions between firms, researchers, scientist and specialised suppliers (Baptista 1998, Hervas-Oliver & Albors-Garrigos 2009). Such links between several actors favour the emergence of knowledge flows and learning processes, thus allowing knowledge exchanges of both formal and informal nature.[11]

Moreover, agglomeration processes tend to support the dissemination of tacit knowledge, that results in more stable and longer joint projects (Baptista 1998, Bennett et al. 2000, Love & Roper 2001).

[9] However, paper's results seem in part contradictory to the ones in Bonander et al. (2016); one may argue that, unlike the latter, this work refers to a public research centre which conducts basic and applied scientific research, as well as technology transfer for market and scientist, for the purpose of pure technological development. Therefore, the increase in patent activity shown by Genoa appears plausible, since the IIT presence leads to a more prominent process of knowledge accumulation than that achievable in presence of a conventional university, with important knowledge spillovers.

[10] Grossman & Helpman (1993) highlight the agglomeration effects induced by localized knowledge spillovers.

[11] See Polanyi (2009), Amin & Wilkinson (1999), Torre & Gilly (2000). Also transport infrastructures may favour innovation: Bottasso et al. (2020), among others, show how larger highway networks tend to make the spatial diffusion of knowledge easier, which in turn tends to foster innovative activity.

Therefore, agglomeration is likely to decrease uncertainty, search costs (Feldman 1999) and transaction costs that firms suffer for joint projects: as a result, firms benefit of increasing returns from collaboration (Izushi 2003, Abramovsky & Simpson 2011, Agrawal et al. 2017).[12]

A more specialized literature this paper contributes to has in turn focused on the impact of universities and public research institutes on innovation and regional growth. Indeed, innovation is primarily affected by new economic knowledge (Audretsch & Feldman 1996) and universities or other public research institutes are traditionally emangmed players that originate and stimulate the transmission of knowledge, thus contributing to industrial innovations (Mansfield & Lee 1996).
Specifically, Nelson (1993), Goldstein et al. (1995) and Drucker & Goldstein (2007) argue how universities and public research organisations are central players in the knowledge production process, emphasizing the mechanisms through which such institutes may potentially have an impact on the regional economic development. Authors mainly refer to the creation of a (local) knowledge base and the development of high-skilled human capital, which in turn fosters further capital accumulation. In this context, public research institutions support technological innovation, attracts other public and private capital investment, fosters the development of a regional leadership and the increase in knowledge infrastructure production and, lastly, influences the regional "milieu".
Finally, knowledge spillovers and human capital development could attract high-tech firms, private sector research laboratories and scientists. Precisely, a face-to-face interaction among public/private research institutions, scientist and firms are essential elements for an effective transfer into production of research findings. This knowledge transfer often supports the creation of start-ups and/or high-tech firm branches in the neighbourhood of a research center. Consequently, regional human capital benefits from the propensity of high-skilled workers to remain and work in the local area; moreover, new scientists and high-quality workers could be attracted from neighbourhood regions, further raising the level of human capital in the area (Rosenberg & Landau 1986).

Despite the theoretical literature is rich, the empirical evidence however is scant and shows a number of conflicting results, possibly in the light of large differences in methodological approaches.
In the most recent literature, the only existing papers that study the relationship between public research institutes and regional economic development, implementing reliable methods for causal inference, are Cowan & Zinovyeva (2013), Kantor & Whalley (2014), Liu (2015), Bonander et al. (2016), Valero & Van Reenen (2019) and Moretti et al. (2019).
In the first paper, by relying on Italian data for 20 Italian NUTS-2 regions between 1984 and 2000 and a first-difference estimation model, Cowan & Zinovyeva (2013) scrutinize whether the expansion of a university system affects local industry innovation. Authors highlight how regional patenting activity increases quite significantly even within five years of a new university opening. Moreover, they find that lagging regions, those with low levels of R&D and human capital investment, are the ones that benefit most from the establishment of a new university, suggesting important heterogeneous effects associated to regional economic characteristics. 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 & Whalley (2014) instead find significant evidences of local spillovers from university research.[13] In 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 research.

[12]The growth theory supports the view for which the non-rivalrous nature of new knowledge explains growth in income per-capita and the presence of increasing returns to scale (Aghion & Howitt 2005, Jones 2005). It is worth noting that New Economic Geography (NEG) literature proposes some theoretical models where location choices and growth are jointly determined. See Black & Henderson (1999), Fujita & Thisse (1996, 2002, 2003), Baldwin & Martin (2004), Minerva & Ottaviano (2009).

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

Similar results can also be found in Liu (2015), who scrutinizes the effects of US land grant universities, established by 1890 Morrill Act, on several economic outcomes, relying on a balanced panel of 1180 U.S. counties from 1840 through 1940. In particular, by leveraging of an event study and a Synthetic Control Method (SCM) approach, the author finds evidence in favour of agglomeration economies and local spillovers from universities, highlighting a huge increase in productivity considering an 80-year period.

While Liu (2015) focuses on the 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 the economy of different regions in Sweden using annual regional-level panel data for the period 1993–2011. Unlike Kantor & Whalley (2014) and Liu (2015), by applying a SCM approach authors find no effects of research universities on local economic performance, on the number of enrolled students, patent applications and firm start-ups, while they report positive effects in research competences, proxied by the number of PhDs and professorships.

Another fundamental contribution is that of Valero & Van Reenen (2019), which relies on region-level European Patent Office (EPO) patents data from the OECD REGPAT database covering 1978 to 2010, as well as regional economic information for 38 countries. By using a five-year differences fixed effect model, authors find that increases in universities' presence are positively correlated with higher regional GDP per-capita. Moreover, the paper suggests knowledge spillovers from universities to geographically close neighbouring regions. They finally argue how the relationship between regional growth and universities may be driven by an increased supply of human capital and greater innovation.

Finally, Moretti et al. (2019), relying on data from 26 OECD countries in the 1987-2009 period and a IV approach, 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.[14] In particular, authors find evidence in favor of a positive impact of public R&D on TFP as well as the presence of spatial spillovers.[15]

3 The Intervention

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 Ministry of Economy and Finance and the Ministry of Education, University and Research and it is located in the city of Genoa as a result of a politic bargaining process.[16] IIT is

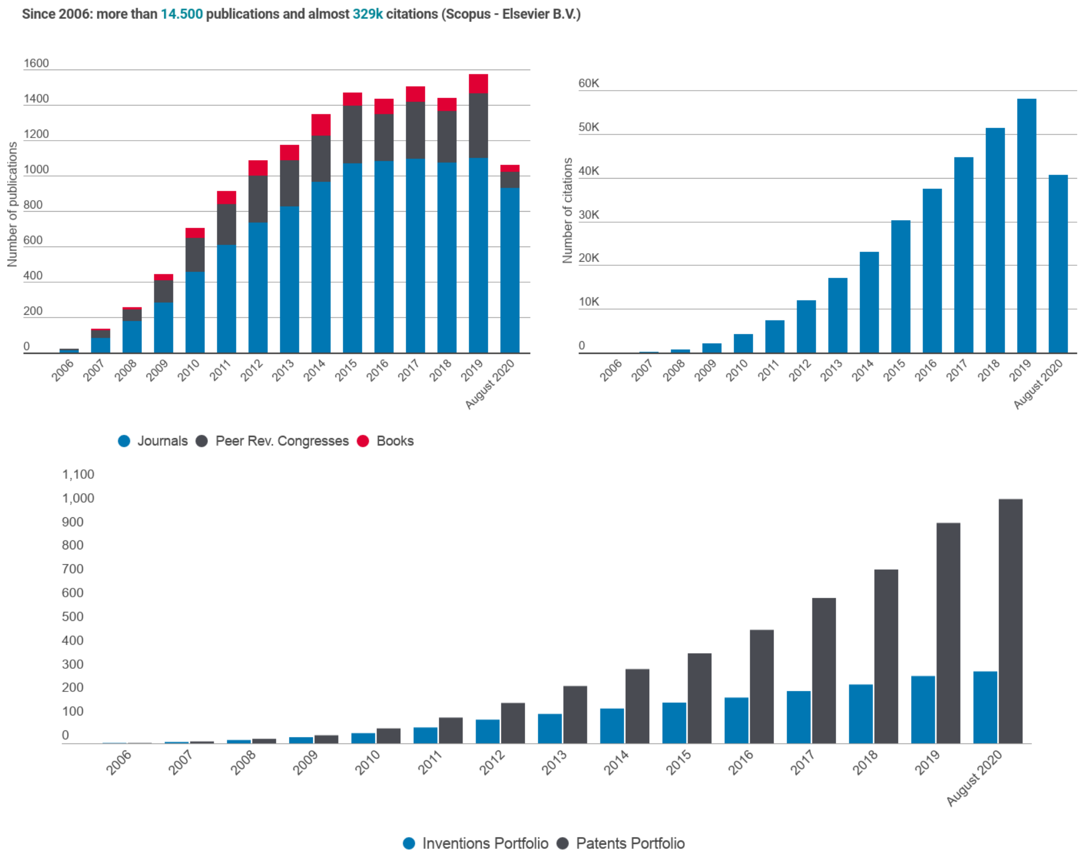
[14] Authors use the variation in defense spending as an instrument.

[15] Similar results for private innovation can be found also in Toole (2012) and Azoulay et al. (2019). Regarding the less recent literature, Beise & Stahl (1999) deal with the impact of publicly funded research on firms' innovative capacity in Germany, finding no higher probability of publicly supported innovations for neighbouring firms. They highlight instead a rise in the absorptive capacity. Acemoglu & Linn (2004) explore the entry of new drugs into medical therapeutic markets, but they do not highlight any evidence supporting science-driven innovation from publicly funded research. Aghion et al. (2009) instead scrutinize the effect of US research universities, finding that exogenous increases in investments in four year college education have a significant impact on growth and patenting. Still considering the US, Hausman (2012) explore the link between university innovation and economic outcomes, highlighting a positive effect of universities on long-run employment and pay for sectors technologically close to the university's research. With an historical approach, Cantoni & Yuchtman (2014) finally argue that ancient medieval German universities played a fundamental role in the commercial revolution.

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

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.
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.[17]

Figure 1: IIT Scientific Production.



Source: `https://www.iit.it/results/publications-talks`

The research organisation of IIT reckon on departments and laboratories, where about 1400 qualified scientist operate in many technological fields such as advanced robotics, drug discovery and development, neuroscience and brain technologies robotics, robotics, brain and cognitive sciences, nanochemistry, nanostructures, nanophysics, pattern analysis and computer vision.[18]

[17]Research take place in Genoa Central Laboratories, at the Centre for Space Human Robotics in Turin; the Centre for Nano-Science and Technology and the Centre for Genomic Science in Milano; the Centre for Neuroscience and Cognitive Systems in Rovereto; the Centre for Nanotechnology Innovation and the Centre for Micro-Biorobotics in Pisa and Pontedera; the Centre for Advanced Biomaterials for Health Care in Naples; the Centre for Biomolecular Nanotechnologies in Lecce; the Centre for Nano-Science in Roma; the Centre for Translational Neurophysiology in Ferrara; the Center for Cultural Heritage Technology in Venice; the LifeTech laboratories in Harvard; the Laboratory for Computational and Statistical Learning at the Massachusetts Institute of Technology, Boston. IIT also has several joint technology laboratories with private companies and public institutes.

[18]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).

In 2018 IIT has attracted public funding of about €91 million, 80% of which has been allocated to technical-scientific activities. In addition, external funding obtained directly from the Foundation has amounted to €340 millions since 2006, of which 71% from competitive projects, 24% from commercial projects and 5% from in-kind projects.
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. In particular, the Institute puts in place a set of services to transfer knowledge from research to the marketplace, especially regarding the changing needs of the high-tech market, i.e. protection of new inventions through intellectual property rights, strategic licensing of IIT technological and scientific knowledge, promotion and support to the origination of innovative start-up companies. Finally, IIT promotes the negotiation and definition of settlements with industries to realize R&D and competitive industrial research, as well as a variety of knowledge dissemination and training activities for the scientific community.[19]
In particular, from 2006 to 2019, IIT's activities have generated a flow of approximately 14500 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 1).[20]

4 Data and Identification Strategy

4.1 Data

This paper relies on annual regional-level panel data for the period 1980–2015 covering all 95 Italian NUTS-3 regions as defined in 1974.[21] In particular, the sample consists of 3420 observations (26 years of pre-intervention data and 10 years of post-intervention data).

For the main analysis, namely the impact of the location of IIT in Genoa (as of 2006) on regional innovation, the analysis primarily relies on a (per-capita) fractional count of patents as a measure of the regional innovation output. Indeed, as recognized by the economic literature, patents represent a fundamental device that allows 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 & Griliches 1980). Finally, as argued by the innovation literature, patents are an effective measure of local technological capacity, although they measure inventions but not all innovative activities (Smith 2005) since not all inventions are patented.
Annual patent data have been recovered 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). 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, the relative technological IPC class of the patent and NACE-2 statistical classification of economic activity.
Raw patent data from EPO-Patstat's bulk datasets are recovered for the period 1980-2015 and processed following the guidelines of OECD Patent Statistics Manual (Zuniga et al. 2009). In order to obtain a measure of regional innovative performances, such data have been aggregated at regional

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

[20] For more details, Appendix A incorporates and expands on the contents of this Section.

[21] The administrative and geographical units considered in the analysis refer to Italian NUTS-3 regions. Since the number of Italian NUTS-3 regions has been progressively changed in recent years, as many new ones are carved out of older ones and several others have been abolished, only the 95 regions that have existed in 1980 (i.e. the beginning of the sample period), those resulting from 1974 administrative settings, have been considered for the main analysis.

NUTS-3 level and the geographic distribution of patent applications has finally been assigned according to the inventor place of residence.[22]
Data are limited to 2015 because of the existence of an underestimation for application counts in the last two years of coverage of the database, due to delays in the publication of EPO data (eighteen/twenty-four months since application or priority date.[23]

Turning to the regional potential for innovation, the dataset includes the number of inventors residing in each region; such measure, obtained from Patstat's raw patent data, is well suited to be a proxy for the regional human capital and knowledge base. Indeed, R&D activities, characterized by a high level of novelty and complexity, are leading sources of innovation which need highly-specialised human capital.

Finally, 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.

Following a consolidated approach in the economic literature (Barro & Sala-i Martin 2004) as well as in SCM studies (Abadie & Gardeazabal 2003, Abadie et al. 2010), a full set of control variables is considered in the analysis. In particular, in order to increase the comparability of treatment and control groups and to refine the quality of impact estimation, the dataset contains several pre-intervention predictor variables referring to features of the university system, industrial performance indexes and economic indicators collected from the "Urban Data Platform+" repository, a joint initiative of the Joint Research Centre (JRC) and the Directorate General for Regional and Urban Policy (DG REGIO) of the European Commission.[24] Specifically, the number of active academic researchers, departments, universities and student enrolments, the number of registered European trade-marks (ETM), Gross Value Added (GVA, for industrial sectors), Gross Fixed Capital Formation (GFCF), the number of worked hours (for industrial sectors), the compensation of employees (for industrial sectors) and the number of employed people are included in the dataset.[25] Territorial-specific features, as population, surface and working age population are also considered.
It is worth noting that not all above-mentioned predictor variables have been included in the analysis, since only those that have a great predictive power on the outcome of interest have been selected by the SCM algorithm (see Section 4.2 for a rationale).

Table 1 illustrates mean values and standard deviations of outcomes and pre-intervention predictor variables, computed for the overall sample (panel A) and for treated and control territories (panels B and C respectively). Descriptive statistics are then reported for the overall time-period, for the specific implementation year 2006 and for the last observational year 2015.
Finally, Figure 2 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). It is worth noting that the left panel of Figure 2 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; to avoid that the innovative capacity of the treated region, i.e. Genoa, may potentially be driven only by IIT's direct patenting activities, the analysis

[22]Therefore, if a patent is characterized by more than one inventor, the patent application is distributed equally between all of them and consequently between their NUTS-3 regions (fractional counting), thus avoiding double counting (OECD 2013). A one has been added to the patent count before taking the log to include observations with values of zero.

[23]See Zuniga et al. (2009) and Bronzini & Piselli (2016) for more details.

[24]See: `https://urban.jrc.ec.europa.eu/rel2018/\#/en/`.

[25]GFCF is defined as in Eurostat (2013).

Table 1: Summary Statistics for Main Variables.

	(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)	13610.00	19140.00	16000.00	22340.00	14930.00	22170.00
GVA (millions)	12310.00	17430.00	14420.00	20120.00	13640.00	20140.00
GFCF (millions)	16930.00	12810.00	22010.00	16340.00	15740.00	12400.00
Worked Hours (Number)	2855.00	2002.00	3065.00	2173.00	2854.00	2068.00
Compensations (millions)	30310.00	27600.00	40710.00	32280.00	44530.00	37250.00
Employed People (Number)	231187.00	266968.00	249655.00	292373.00	244767.00	307762.00
Population (Number)	570284.00	588493.00	577414.00	596769.00	600171.00	642943.00
Surface (sq. KM)	2917.00	1555.00	2917.00	1555.00	2917.00	1555.00
Working Age Population (Number)	376573.00	392059.00	378534.00	397547.00	387225.00	420848.00
Univerity Enrolments (Number)	18135.00	34499.00	19136.00	35734.00	-	-
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	-	-

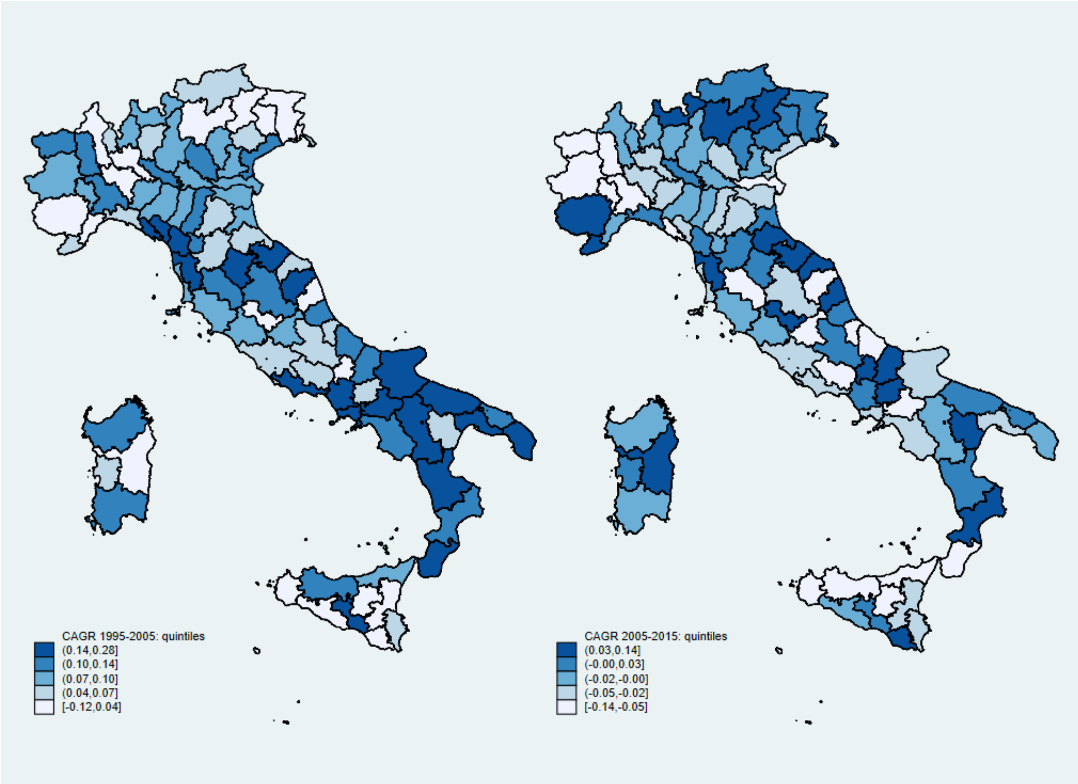
	(B) Treated Unit					
Variables	mean	sd	2006	sd	2015	sd
Patents (Fractional Count)	53.06	30.07	90.39	0.00	81.33	0.00
Inventors (Number)	100.40	67.95	165.00	0.00	204.00	0.00
European Trade Marks (Number)	36.50	41.34	77.00	0.00	112.00	0.00
GDP (millions)	23600.00	2442.00	26410.00	0.00	24670.00	0.00
GVA (millions)	21690.00	1866.00	23790.00	0.00	22390.00	0.00
GFCF (millions)	7505.00	597.20	7830.00	0.00	6360.00	0.00
Worked Hours (Number)	1189.00	49.63	1193.00	0.00	1097.00	0.00
Compensations (millions)	12910.00	3699.00	16230.00	0.00	17950.00	0.00
Employed People (Number)	371892.00	14727.00	381142.00	0.00	387330.00	0.00
Population (Number)	926585.00	60407.00	876579.00	0.00	861253.00	0.00
Surface (sq. KM)	1806.00	0.00	1806.00	0.00	1806.00	0.00
Working Age Population (Number)	571323.00	46787.00	541225.00	0.00	520119.00	0.00
Univerity Enrolments (Number)	35505.00	2513.00	35110.00	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)	13500.00	19210.00	15880.00	22430.00	14830.00	22270.00
GVA (millions)	12210.00	17500.00	14320.00	20210.00	13550.00	20230.00
GFCF (millions)	17030.00	12840.00	22160.00	16360.00	15840.00	12430.00
Worked Hours (Number)	2872.00	2005.00	3085.00	2176.00	2873.00	2071.00
Compensations (millions)	30490.00	27690.00	40970.00	32350.00	44820.00	37350.00
Employed People (Number)	229641.00	268017.00	248210.00	293662.00	243200.00	309098.00
Population (Number)	566494.00	590429.00	574231.00	599158.00	597394.00	645817.00
Surface (sq. KM)	2929.00	1559.00	2929.00	1559.00	2929.00	1559.00
Working Age Population (Number)	374423.00	393650.00	376804.00	399318.00	385811.00	422878.00
Univerity Enrolments (Number)	17949.00	34634.00	18966.00	35887.00	-	-
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: Data refers to 95 Italian NUTS-3 regions, in accordance with the NUTS-3 administrative setting of 1974, observed from 1980 to 2015. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. Panel A refers to the overall sample, panel B refers to Genoa (Treated region), while panel C refers to the remaining 94 regions (Donor Pool). Descriptive statistics are reported for the overall time-period, for the specific implementation year 2006 and for the last observational year 2015.

also relies on a specific sub-sample; in the latter all patents that refer to the IIT have been identified and dropped. Also inventors that belong to IIT are not considered in the specific measure of regional

Figure 2: Italian Patent Activity. Patent Fractional Count (growth rates).



Notes: Cumulative Average Growth Rates (CAGR) of the innovative capacity of Italian regions, in accordance with the NUTS-3 administrative setting of 1974. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. 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.

human capital.[26] It should be noticed that this exercise allows to scrutinize potential local knowledge spillovers from IIT to geographically closer neighbouring firms.

4.2 The SCM Method

While IIT's public and private research funding can be accurately measured, the overall innovative and economic impact of its implementation on the hosting region is much more difficult to estimate. In this context, a fundamental issue for causal inference is to compare trends over time in the outcome of interest for Genoa with those of a control group of unaffected regions. However, one must face some typical problems in performing this exercise.

First, Genoa is the unique treated region: in particular, this aspect discourages the use of a Difference-in-Differences (DiD) approach, since this identification strategy does not perform well when treated units are limited to only one. Indeed, as argued by Conley & Taber (2011), 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.[27] Therefore, classical inference can be misleading. Likewise, although it is a suitable approach to choose from the donor pool those control units that are most similar to treated ones before the treatment, Propensity Score Matching (PSM) is nevertheless not feasible when there is only one treated unit.

[26] See Section 5.2 and 5.3 for a rationale.

[27] This problem is exacerbated if standard errors are not corrected for small sample units (Conley & Taber 2011).

Second, it is worth noting that, in general, the choice of which region receives the treatment might be not necessarily random.
Third, economic outcomes are not necessarily the same across regions in the absence of the treatment.[28] Moreover, a DiD approach does not allow the effects of confounding unobserved characteristics to vary with time.

Therefore, addressing these concerns involves a correct choice of the control group for a proper policy evaluation, thus developing a reliable estimate of what Genoa would have been in the absence of the treatment.[29]
To this end, in this work the Synthetic Control Method (SCM) for comparative case studies (Abadie & Gardeazabal 2003, Abadie et al. 2010, 2015) is implemented to estimate the effects of IIT research on regional innovative and economic performances. Such approach identifies the location of IIT central laboratories in Genoa in 2006 as a natural experiment. Indeed, the designation of Genoa as IIT headquarter has been affected by many factors, arguably exogenous, different from economic considerations.[30] After controlling for the absence of confounding factors, the institution of IIT in 2006 thus represents a probably exogenous policy change that allows the identification of the causal effect of public funded research centres on local innovative capacity and growth.[31]
In particular, a combination of other unaffected Italian NUTS-3 regions, the so-called donor pool, is used in order to construct a “synthetic" control that mimics Genoa before the implementation of IIT; 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 the outcome of interest. The resulting evolution of the synthetic Genoa compared to the real one is finally used to measure the impact of the IIT.

Formally, the sample consists of a balanced panel with 95 Italian NUTS-3 regions, indexed by j, among which region $j = 1$ is Genoa and units $j = 2,3,\ldots,95$ represent the set of control units that are not exposed to the treatment (donor pool). Italian regions are observed in years $t = 1980,1981,\ldots,2015$, of which those before 2006 represent the pre-intervention period T_0, while those after 2006 constitute the post-intervention period T_1, with $T = T_0 + T_1$.
Assume that $W = (w_2,\ldots,w_{95})'$ is a (94×1) vector of weights, with $0 \leq w_j \leq 1$ for $j = 2,3,\ldots,95$ 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 the values of the same variables for the donor pool. Let $Y_{j,t}$ be the outcome 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 the outcome of interest for the treated unit, while $Y_{j,t}(0)$ is the $(T_1 \times 94)$ matrix collecting post-intervention values of the outcome of interest for units in the donor pool.

In the spirit of Rubin (2005), if one considers two potential outcomes, namely $Y_{Genoa,t}(1)$ as the outcome 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 regions in the donor pool, $j = 2,3,\ldots,95$, the "synthetic control".
The "synthetic Genoa" is characterized by the weighting vector W; precisely, the set of optimal weights

[28] Indeed, if the treated region does not share similar economic characteristics and economic trends in the pre-treatment period with respect to control ones, a comparison between them is likely to produce biased estimates.

[29] This involves estimating a (counterfactual) change over time for Genoa if the policy change has not occurred.

[30] See Section 3.

[31] Comfortingly, other important place-based innovation policies that might blur the effect of IIT did not occur in Genoa.

W^* is computed so that the "synthetic Genoa" best approximates the real Genoa, exposed to the intervention, with respect to the pre-intervention outcome predictors and a linear combination of pre-intervention outcomes. Optimal weights w_j^* are the ones that minimize $\sum_{m=1}^{k} \vartheta_m (X_{1,m} - X_{0,m} W)^2$, 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 Mean Squared Prediction Error (MSPE) of the synthetic control estimator.[32]

Therefore, the treatment effect for Genoa at time $t \in T_1$ is calculated as the difference between the outcome 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 approach has many advantages, both in terms of transparency and robustness of identification assumptions. Besides being a useful econometric approach when only one unit experiences the treatment and the other ones do not, the SCM relies on the DiD framework but is more sophisticated; indeed, by implementing a weighted average of all controls, such method systematically offers comparisons that are more appealing with respect to DiD and other matching techniques. Indeed, the SCM overcomes the use of a single control unit or a simple average of control units.[33] 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 the outcome of interest, thus improving the quality of the estimation. Further, in similar contexts the SCM approach overcomes DiD frameworks, allowing for the presence of unobserved confounders that are not constant in time (Abadie et al. 2015).
The SCM approach also has some limitations. The main concern relates to possible confounding policies, contemporaneous to the implementation of the IIT, which may have influenced outcomes of interest. In this case, the estimated impact of the IIT could be biased. Rather comfortingly, as far as is known, other important place-based innovation policies, around 2006, which may have blurred the effect of the IIT, did not occur in Genoa. In particular, until 2015 the institution of IIT was arguably the most prominent place-based innovation policy which has ever been implemented in Italy, thus limiting this potential source of bias in our exercise.
Moreover, another key limitation of the SCM identification strategy is that there is no clear approach to the choice of pre-intervention predictors variables that should be used to estimate the synthetic control. This lack of guidance could lead to significantly different choices of these variables, with the associated opportunity to choose "statistically significant" specifications even when in reality there is no effect. This arbitrariness in the choice of the estimation model substantially implies a some discretionary power for the scholar to construct the counterfactual for the treated unit and, therefore, the estimated treatment effect: this could potentially undermine one of the main advantages of the SCM approach, i.e. a purely data-driven process. In order to alleviate such concern, the best fitting matching specification has been selected by choosing the model that minimizes the pre-intervention Root Mean Square Prediction Error (RMSPE).[34]

[32] The Mean Squared Prediction Error is the expected value of the squared difference between the fitted values implied by a predictive function $\widehat{g}$ and the values of a (unobservable) function g. It is an inverse measure of the explanatory power of $\widehat{g}$ and can be used in the process of cross-validation of an estimated model.

[33] For example, propensity score matching is infeasible when there is only one treated unit.

[34] The predictor variables used in this work are a set of pre-intervention region-specific characteristics and pre-intervention outcome variables, which are described in detail in Section 4.1. It is worth noting that not all predictor variables included in the dataset are considered, as the RMSPE optimization algorithm tends to eliminate those with less predictive power. Similar to MSPE, the RMSPE is a measure of the quality of a predictor. Researchers can evaluate the goodness of fit by calculating the RMSPE between the real and the synthetic region during the pre-treatment period. A poor fit might be caused by many factors, as i.e. weak predictors.

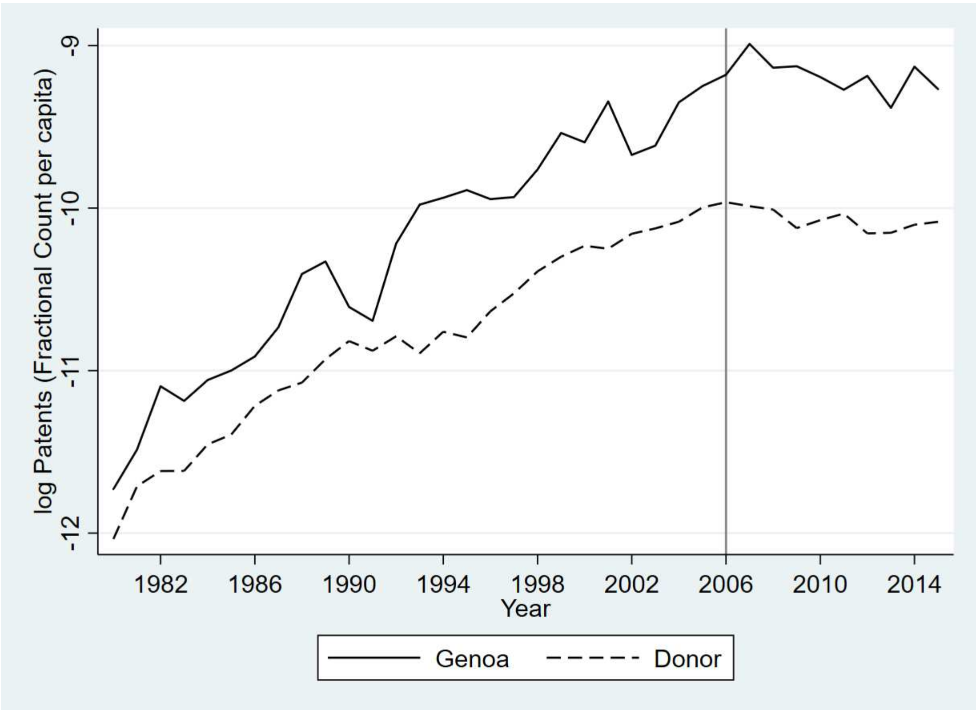
Finally, in studies applying SCM methods, asymptotic inference cannot be performed. Therefore, to address such concern, "in-space placebos" and "in-time placebos" tests are proposed.[35]

5 Empirical Results

5.1 Impact on Regional Innovation

The regional innovative performance, measured by the (log) per-capita number of patents (fractional counting), is first considered: simple graphical evidence is provided in Figure 3, in which such measure 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.

Figure 3: Descriptive Evidence. Innovative Capacity.



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.

The two lines seem to show a parallel trend, although the innovative performance of Genoa is higher with respect to the donor pool. In addition, a slight positive divergence in the number of patents per-capita in Genoa after 2006 can be noted.

The descriptive evidence inferred from the simple representation in Figure 3 is further investigated by estimating a standard DiD model to detect the impact of IIT. Indeed, despite being aware of concerns about such identification strategy, as argued in Section 4.2, it seems useful to provide some preliminary evidence of the impact of the treatment, as columns from (1) to (4) of Table 2 show. Moreover, in columns from (5) to (8) results from the estimation of a specification that includes lags à la Autor (2003) are reported: the latter, where $Post_{t=2006,2007,...,2011+}$ assumes the value of 1 in the specific year t and 0 otherwise, allows IIT's activities to generate different effects over time.[36]

[35] See Section 5.2 for details.

[36] The DiD model is built like $\log Innov_{i,t} = \alpha_i + \beta(Genoa_{i,t} * Post_{i,t}) + \mu_i + \tau_t + \epsilon_{i,t}$, where $\log Innov_{i,t}$ is Patent Fractional Count (log) per-capita and the parameter of interest, β, is associated to the inter-

Table 2: DiD Estimates. Innovative Capacity.

Dependent Variable *Patents (log) per-capita*	(1) FULL SAMPLE	(2) FULL SAMPLE	(3) SUB SAMPLE	(4) SUB SAMPLE	(5) FULL SAMPLE	(6) FULL SAMPLE	(7) SUB SAMPLE	(8) SUB SAMPLE
$Genoa * Post_{2006}$	0.323***	0.318***	0.270***	0.265***				
	(0.0349)	(0.0348)	(0.0346)	(0.0346)				
$Genoa * Post_{2006}$					0.225***	0.221***	0.225***	0.221***
					(0.0371)	(0.0381)	(0.0371)	(0.0381)
$Genoa * Post_{2007}$					0.440***	0.435***	0.441***	0.436***
					(0.0459)	(0.0475)	(0.0458)	(0.0474)
$Genoa * Post_{2008}$					0.314***	0.312***	0.301***	0.300***
					(0.0441)	(0.0451)	(0.0441)	(0.0450)
$Genoa * Post_{2009}$					0.437***	0.433***	0.416***	0.412***
					(0.0462)	(0.0471)	(0.0462)	(0.0471)
$Genoa * Post_{2010}$					0.322***	0.312***	0.295***	0.285***
					(0.0426)	(0.0431)	(0.0425)	(0.0430)
$Genoa * Post_{2011+}$					0.299***	0.293***	0.205***	0.199***
					(0.0397)	(0.0395)	(0.0394)	(0.0391)
Regions FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
IIT Patents	✓	✓	✗	✗	✓	✓	✗	✗
IIT Sec. Lab	✓	✗	✓	✗	✓	✗	✓	✗
Observations	3,420	3,276	3,420	3,276	3,420	3,276	3,420	3,276
Adjusted R-squared	0.890	0.887	0.891	0.887	0.890	0.887	0.890	0.887
F Test (p-value)	0	0	0	0	0	0	0	0

Notes: Columns from (1) to (4) show results of the estimation of a traditional DiD model with panel data, built like $\log Innov_{i,t} = \alpha_i + \beta(Genoa_{i,t} * Post_{i,t}) + \mu_i + \tau_t + \epsilon_{i,t}$, where the dependent variable is (log) Patents (fractional count) per-capita and the variable of interest, β 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 from (5) to (8) show results from the estimation of a specification that includes lags à la Autor (2003), built like $\log Innov_{i,t} = \alpha_i + \sum_{j=0}^{5+} \beta_j (Genoa_{i,t} * Post_{i,t+j}) + \mu_i + \tau_t + \epsilon_{i,t}$: $Post_{t=2006,2007,...,2011+}$ assumes the value of 1 in the specific year t and 0 otherwise. The sub-sample does not include IIT own patents and 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 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

In particular, results in column (1) of Table 2 suggest a positive and statistically significant impact of IIT on the innovative performance of Genoa with respect to all remaining Italian regions (with an estimated effect of about 38%); such result is confirmed when regions with main IIT secondary laboratories are excluded from the analysis (column 2) and when the sub-sample is considered (columns 3 and 4, where the estimated effect settles at about 31%). Turning to the estimation of the specification with lags à la Autor (2003) in columns from (5) to (8), it should be stressed that all the parameters are positive and statistically significant, thus suggesting a positive impact of the research conducted by IIT from the year of implementation (2006) until five years and onward.

However, it is necessary to refrain from interpreting such results as a causal effect. Indeed, as

action 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. The specification that includes lags à Autor (2003) is built like $\log Innov_{i,t} = \alpha_i + \sum_{j=0}^{5+} \beta_j (Genoa_{i,t} * Post_{i,t+j}) + \mu_i + \tau_t + \epsilon_{i,t}$, where $Post_{i,t+j}$ assumes the value of 1 in the specific year $t+j$ and 0 otherwise. The specification with lags à la Autor (2003) allows to scrutinize the possibility that the effects of the treatment speed up, stabilize, or mean revert over time. In order to lower the number of parameters of the model, the paper estimates the effect of IIT from the implementation year ($t = 2006$) until five years later and onward ($t = 2011+$). The analysis is repeated on several sub-samples, which take into account both the presence of IIT secondary laboratories in several Italian regions (whose observations have been excluded in even columns) and the patent activity directly conducted by the IIT (columns 3, 4, 7 and 8), that may drive regional innovation, generating biased estimates: in such sub-sample all patents that refer to the IIT have been identified and dropped. See Section 4.1 and Section 5.2.

discussed in Section 4.2, estimates in Table 2 could be potentially biased from the presence of a single treated unit or by the different choices carried out to identify the control group. The SCM method addresses these identification concerns, building a reliable counterfactual that is characterized by a strong similarity in structural characteristics with Genoa.

Table 3 shows region weights (left panel) and predictor balance (right panel). The SCM delivers positive critical weights on several donor pool regions; in particular, patent activity trend in Genoa, prior to the implementation of IIT, is best reproduced by a combination of 16 Italian regions.[37] Moreover, in the right panel of Table 3 the set of predictor variables of the treated unit (Genoa) and the average of the synthetic Genoa built through the SCM are reported. Specifically, the set of pre-treatment predictor variables that minimize the RMSPE refers to the overall mean and several lags of the outcome variable (ten lags, from 1996 until 2006), the number of inventors in the region (overall mean and 10 lags) and the overall mean of GDP, GVA, worked hours and number of university departments in the region. As clearly shown in Table 3, the synthetic Genoa closely mimics the real one both in terms of patents per-capita and in other predictor variables, thus possibly contributing to the creation of a reliable counterfactual.[38]

Results are reported in Table 4 and Figure 4. In particular, Table 4 is aimed to depict the magnitude of the impact of the IIT on the innovative capacity of Genoa for the whole post-treatment period (2006-2015). 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. Causal effect estimates suggest annual gaps that range from a minimum of 6.11 (7.53%) to a maximum of 35.90 (39.69%) more patents per million inhabitants.

Figure 4 provides instead graphical evidence by comparing the trend of the innovative capacity of Genoa and the synthetic control over 36 years. The synthetic control closely matches the innovative evolution of Genoa in the pre-intervention period, except for a small period (1990-1994) not in proximity to the intervention (as confirmed by predictor balance in Table 3). In particular, the treated unit and its synthetic equivalent are very likely to be similar in the period prior the implementation of IIT, underlining the credibility of SCM as counterfactual estimator.

The joint analysis of Figure 4 and Table 4 suggests that, on average, the establishment of IIT impacts on the innovative capacity of Genoa by about 22.5 more patents for million inhabitants every year (24.37% higher with respect to the synthetic Genoa). In particular, 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.

Overall empirical results seem to be aligned to Cowan & Zinovyeva (2013) and Liu (2015)'s ones, suggesting that the location of new public funded research centres improves regional innovative capacity and productivity, with effects largely caused by the high quality scientific research.

These empirical findings can be also explained by the main predictions of innovation literature. In particular, it is widely recognised that knowledge is a key driver of innovation (Audretsch & Feldman 1996, Mansfield & Lee 1996); the latter is arguably affected by the dynamics of groups working on innovative projects, the characterization of the process through which innovation is generated and im-

[37]Specifically, Vercelli, Aosta, Como, Milano, Pescara, Caserta, Napoli, Avellino, Brindisi, Padova, Modena, Ferrara, Foggia, Potenza, Palermo and Siena.

[38]Table 3 shows a fundamental characteristic of SCM approach; unlike other matching estimators, the SCM forces scholars to prove the similarity among areas exposed to the treatment and their synthetic counterparts, that is, the weighted average of units in the donor pool. Consequently, the SCM prevents the estimation of "extreme counterfactuals", that are those that fall far outside the convex hull of the data (King & Zeng 2006).

Table 3: Effect of the Location of IIT in 2006. Innovative Capacity. Predictor Balance and Region Weights.

Region	Weight	Predictor 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
Milano	.022	log Patents (per-capita 2002)	-9.672	-9.546
Modena	.068	log Patents (per-capita 2003)	-9.616	-9.588
Napoli	.032	log Patents (per-capita 2004)	-9.349	-9.374
Padova	.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: 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. The set of pre-treatment control variables refers to the overall mean and several lags of the outcome variable (ten lags, from 1996 until 2006), the number of inventors in the region (overall mean and 10 lags) and the overall mean of GDP, GVA, worked hours and number of university departments in the region.

Table 4: Effect of the Location of IIT in 2006. Innovative Capacity. Effect Estimates.

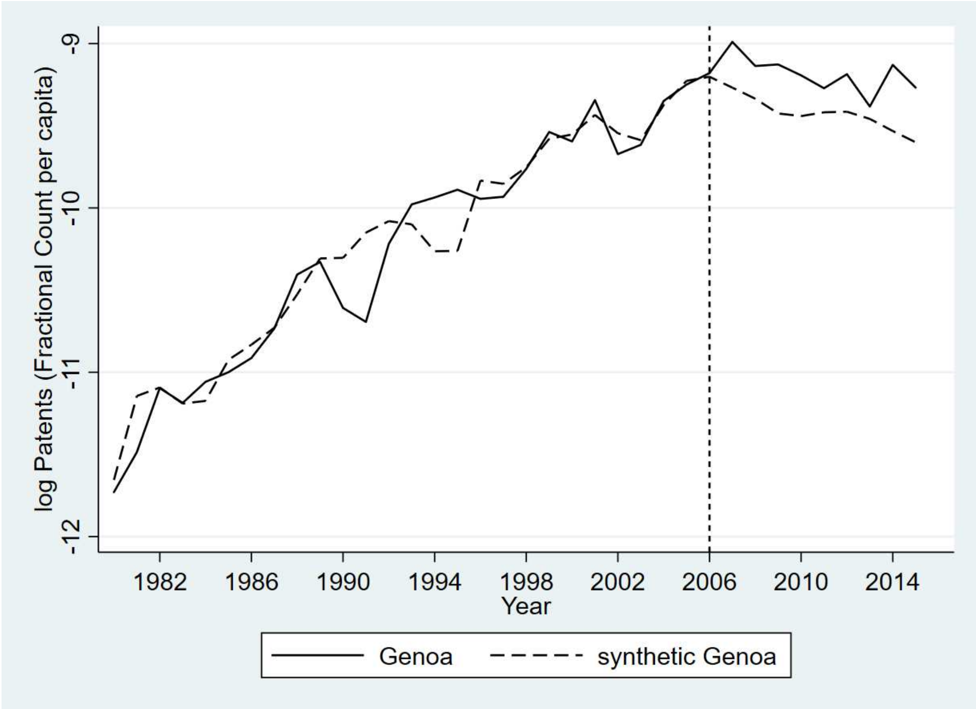
Year	log Patents - Treated (FC per-capita)	log Patents - Synthetic (FC per-capita)	Patents - Treated (FC million inhabitants)	Patents - Synthetic (FC million inhabitants)	Absolute Effect	Relative Effect
2007	-8.9896	-9.2681	124.70	94.39	30.31	27.67%
2008	-9.1361	-9.3356	107.71	88.23	19.48	19.89%
2009	-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. The specification includes the overall mean and several lags of the outcome variable (ten lags, from 1996 until 2006), the number of inventors in the region (overall mean and 10 lags) and the overall mean of GDP, GVA, worked hours and number of university departments in the region. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. 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.

plemented, the organizational factors that induce/inhibit the innovative performance of firms, R&D collaboration and networks, the dynamics of innovation dissemination within and across industries, the workings of the national/regional innovation systems and the institutional environment (Fisher et al. 2009).

In this context IIT specifically conducts basic and applied scientific research for the purpose of pure technological development, arguably favouring the process of exploratory search, supporting the cre-

Figure 4: Effect of the Location of IIT in 2006. Innovative Capacity. SCM.



Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual. The specification includes the overall mean and several lags of the outcome variable (ten lags, from 1996 until 2006), the number of inventors in the region (overall mean and 10 lags) and the overall mean of GDP, GVA, worked hours and number of university departments in the region. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. The weights used to build the synthetic control and the predictor balance are shown in Table 3. The causal impact of the creation of IIT on innovation is measured as the difference in the number of patents between the treated region and its synthetic counterpart in the period after the 2006 intervention.

ation of a knowledge base by engaging in more basic and risky research.[39] Moreover, one of IIT's primary goal is to transfer own technology research results to the productive fabric. In particular, IIT's technology transfer refers to the protection of new technologies and innovations through patents and copyright rights, as well as the strategic licensing of IIT's knowledge. It is worth noting that IIT also supports the creation of new start-ups and researchers' spin-offs, as well as the definition of agreements with private firms to carry out R&D and competitive industrial researchers, thus supporting knowledge accumulation.

Therefore, the estimated positive impact of IIT is likely to be due to a variety of economic mechanism, in particular agglomeration economies working through the attraction of high-skilled human capital and high-tech firms within the region, which in turn spur innovation. Moreover, IIT may fills gaps in research infrastructures. However, such knowledge accumulation process is not a sufficient condition for increased regional innovative performances. Indeed, absorptive capacity is also a fundamental issue to foster innovation, as argued, among others, by Cohen & Levinthal (1990), Lane & Lubatkin (1998) and Lane et al. (2001). Nevertheless, IIT also supports a variety of knowledge sharing activities, aimed to foster 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 further favours knowledge accumulation, knowledge spillovers, thus allowing

[39]It is worth noting that the ability to exploit new knowledge and technologies depends on the preventive exploration of the latter.

the transmission, transformation, absorption and utilization of the regional knowledge base.
It is worth noting that estimates could also be seen as contradictory with respect to results in Bonander et al. (2016), since authors find no impact of new granting research universities on the Swedish regional economy. In particular, authors highlight that the intervention has caused a rise in awarded PhDs and professorships, whereas no effects are detected for the number of students, patent applications, and firm start-ups. However, this divergence can easily be explained by the different nature inherent in the institutions under scrutiny.[40]

One potential concern in the context of this study is that results might be underestimated, due to the influence of the 2008 financial crisis; indeed, such financial shock may have constrained patent activities, as extensively shown in the economic literature.[41] In particular, in early stages of the 2008 financial crisis, the Genoese local economy has been affected less harshly with respect to other similar areas, due to several structural factors that tend to moderate the sensitivity of Genoa (and Liguria) to fluctuations of economic cycle. Specifically, such factors refer to the higher level of tertiarisation, to the low level of openness to international trade, the relevant proportion of household income from pensions and public salaries. However, during the following years and with the extension of crisis' effects from the financial side to the real economy, Genoa has also been largely hit, leading to significant contractions in consumption, investments and employment levels, a decrease in disposable income for households, a decrease in bank lending and a substantial growth in impaired loans (Bankitalia 2016).[42]
Therefore, although one can be confident that the economic structure of the area is sufficiently controlled through the SCM specification, it is necessary to taking into account the possibility of an underestimation in coefficient estimates. Nevertheless, it is worth noting that, as displayed in Figure 4, during this period, Genoa suffers from a slowdown in patent activity, like its synthetic counterpart, but still remains at a higher levels, thus still corroborating the hypothesis of a positive and significant impact of IIT on the regional innovative capacity.

Finally, it is worth noting that innovation can be also displaced from one region to another, potentially generating a zero-sum game among regions and suggesting a spatial reorganization of economic activity rather than a pure net economic effect. However, in the construction of the synthetic Genoa positive weights are never assigned to neighbouring regions, possibly alleviating the concern of such potential source of bias.[43]

5.2 Robustness Analysis

In order to verify the validity of paper's results, a series of additional robustness checks, placebo and sensitivity tests are carried out.

First, it is verified whether main results are sensitive to the exclusion of some regions. In particular, the SCM only applies positive weights to certain donor pool's units, and one might argue that estimates could be driven by the specific innovative performance of a single region.
The top panel of Figure 5 shows SCM's results after excluding the region of Ferrara, that has the

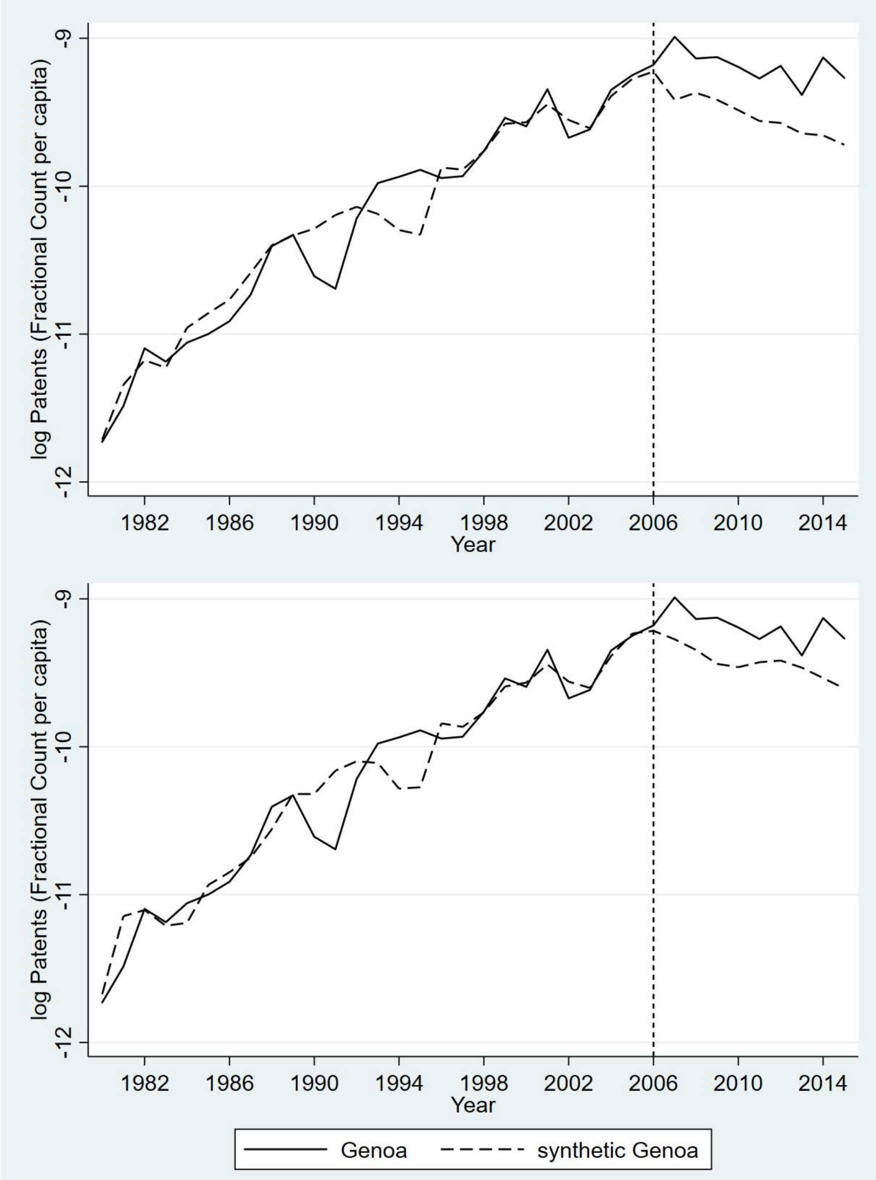
[40]In particular, despite universities are central players for knowledge accumulation, basic research and creation of high-skilled workers, IIT specifically conducts basic and applied scientific research for the purpose of pure technological development and transfer of the latter to the productive fabric, thus fostering the innovative capacity of the treated region.

[41]The lack of financial resources origins R&D underinvestments, causing lower levels of innovation and, consequently, a slowdown in patenting activities. For details, see Benoliel & Gishboliner (2014).

[42]For details, see `https://www.bancaditalia.it/pubblicazioni/economie-regionali/2009/2009-0027/index.html?com.dotmarketing.htmlpage.language=1` and `https://www.bancaditalia.it/pubblicazioni/economie-regionali/2010/2010-0050/index.html?com.dotmarketing.htmlpage.language=1`.

[43]However, the issue would deserve further attention, possibly with a General Equilibrium analysis.

Figure 5: Effect of the Location of IIT in 2006. Innovative Capacity. Robustness.



Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and the synthetic Genoa 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). The specification includes the overall mean and several lags of the outcome variable (ten lags, from 1996 until 2006), the number of inventors in the region (overall mean and 10 lags) and the overall mean of GDP, GVA, worked hours and number of university departments in the region. Predictor balance and region weights, not reported, are available on request. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero.

highest value in the weighting matrix computed by the algorithm that creates the synthetic control (see Table 3 in Section 5.1).[44] The bottom panel of Figure 5 provides 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.[45] Rather

[44]Predictor balance and region weights, not reported, are available on request.

[45]In particular, the regions where the four major IIT research sites, measured in terms of human resources, are excluded (see Figure A.1 in Appendix for details). Predictor balance and region weights,

comfortingly, innovative patterns shown in Figure 5 are quite similar to those in the baseline specification: after 2006 a significant positive effect is observed, suggesting the absence of different dynamic patterns between Genoa and its synthetic counterpart.

Second, a further potential concern is that main results may be driven by IIT's own patent activity, an issue that might blur the effect of technological and knowledge spillovers from IIT's on the local innovation milieu.[46]

Hence, to alleviate such concern, all patents that refer to the IIT have been identified and dropped from the sample (see Section 4.1). The SCM approach has therefore been replicated on such sub-sample.

Table 5: The Effect of the Location of IIT in 2006. Innovative Capacity. Sub-Sample. Predictor Balance and Region Weights.

Region	Weight	Predictor 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
Milano	.022	log Patents (per-capita 2002)	-9.672	-9.546
Modena	.068	log Patents (per-capita 2003)	-9.616	-9.588
Napoli	.032	log Patents (per-capita 2004)	-9.349	-9.374
Padova	.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: The Table shows predictor balance and region weights for the specification that analyses the impact of IIT on the innovative capacity relying on the sub-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.

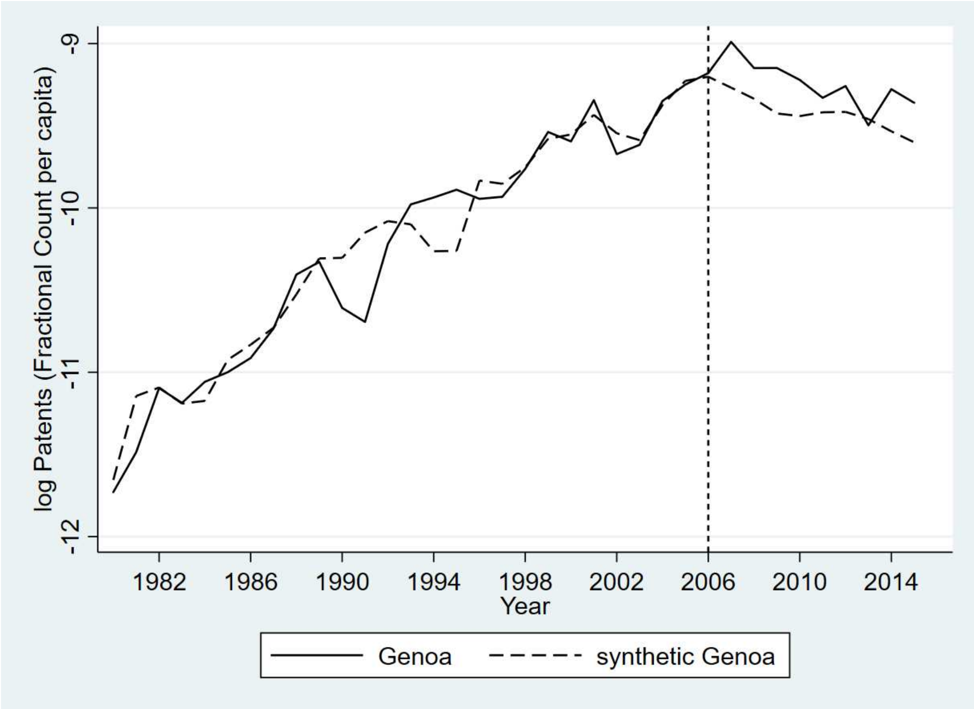
Results are shown in Figure 6 and Table 6, while Table 5 usually provides predictors balance and region weights. Findings in Figure 6 are similar to those in the baseline specification. In particular, regarding the quality of fit in the pre-intervention period, nothing appears to have significantly changed. Moreover, predictor balance (Table 5) remains reasonably similar in the treated region and the synthetic versions for all pre-treatment predictor variables.

The joint analysis of Table 6 and Figure 6 allows to highlight that, after the creation of IIT, Genoa

not reported, are available on request.

[46] In particular, IIT implements an international model of public research that specifically focuses on the development of technologies for the market. IIT own research, both basic, "curiosity-driven" and applied, has thus led to file a large number of patents in different study areas defined by 4 research domains (see Section 3).

Figure 6: Effect of the Location of IIT in 2006. Innovative Capacity. Sub-Sample.



Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual. Sub-sample: all patents that refer to the IIT have been identified and dropped from the analysis. The specification includes the overall mean and several lags of the outcome variable (ten lags, from 1996 until 2006), the number of inventors in the region (overall mean and 10 lags) and the overall mean of GDP, GVA, worked hours and number of university departments in the region. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. The weights used to build the synthetic control are reported in Table 5, as well as the predictor balance.

Table 6: Effect of the Location of IIT in 2006. Innovative Capacity. Effect Estimates. Sub-Sample.

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%

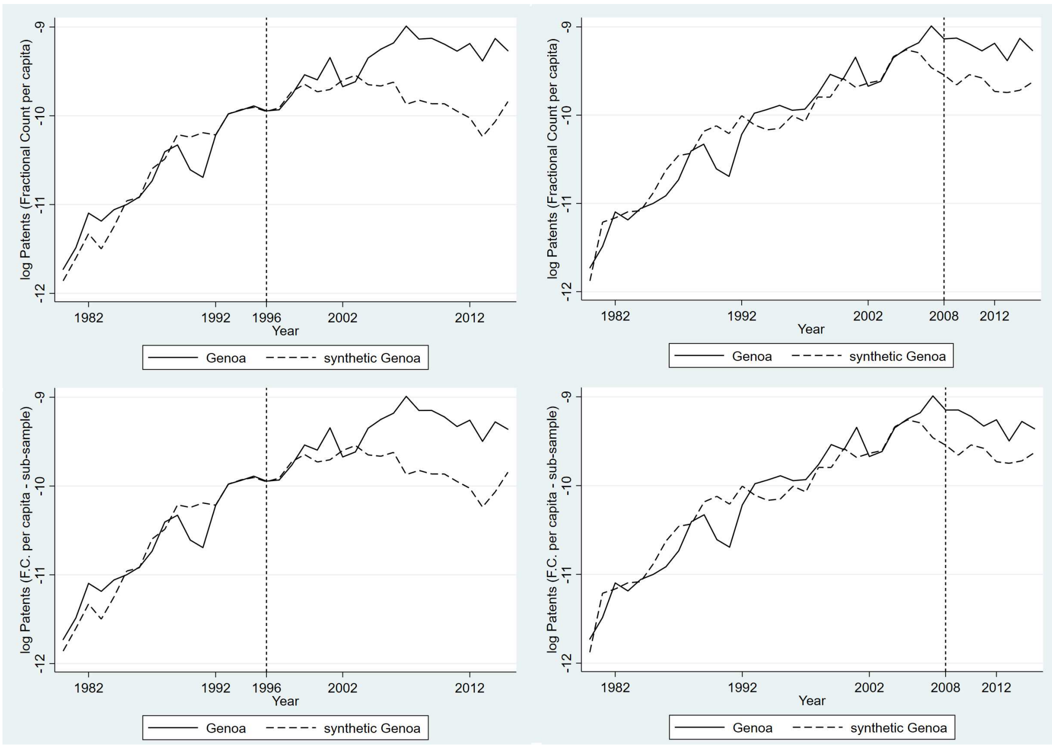
Notes: Innovative capacity, proxied by (log) Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual. The specification includes the overall mean and several lags of the outcome variable (ten lags, from 1996 until 2006), the number of inventors in the region (overall mean and 10 lags) and the overall mean of GDP, GVA, worked hours and number of university departments in the region. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. 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. Sub-sample: all patents that refer to the IIT have been identified and dropped from the analysis.

tends to have about 16.86 more additional patents per millions inhabitants every year (18.43% higher with respect to the synthetic Genoa); moreover, outcome's trends are quite similar to those previously analysed in the baseline specification. In particular, effect estimates range from 7.50 (8.82%) to 30.31 (27.67%) more patents every million inhabitants: these results suggest (despite the smaller magnitude) a positive and significant impact of IIT on the innovative capacity of Genoa, thus confirming results in Section 5.1.

Moreover, by dropping patents that are directly produced by IIT and preserving remaining industrial ones, this exercise allows to disentangle spillover effects of IIT from the direct impact of such institution on patenting. Therefore, this finding suggests the existence of local knowledge spillovers from IIT to the Genoese innovation milieu. In particular, such effect may be due to a variety of economic mechanism, as agglomeration economies working through the attraction of high-skilled human capital and high-tech firms within the treated region (the topic is handled in Section 5.3). 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, thus further enhancing regional innovation.

A final concern is that, for SCM estimators, asymptotic inference cannot be performed.[47] Therefore, to address such issue, "in-space placebos" and "in-time placebos" tests are proposed to assess the robustness of previous results. Indeed, the level of confidence about the validity of paper's results would vanish if the SCM also estimated large impacts when implemented to to years when the intervention did not occur or, alternatively, to regions that did not receive the treatment (Heckman & Hotz 1989, Abadie et al. 2015).

Figure 7: Effect of the Location of IIT in *Fake* Years. Innovative Capacity. Falsification Test.



Notes: Innovative capacity, proxied by log Patents (fractional count) per-capita, of the treated region (Genoa) and its synthetic counterfactual. Sub-sample: all patents that refer to the 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 the left panel *fake* implementation year 1996 is presented. In the right panel *fake* implementation year 2008 is presented.

First, in the spirit of common falsification tests, a "in-time placebo" test is performed. In the latter main specifications are performed by shifting the timing of the treatment: in particular, such falsification test assumes the realization of IIT in *fake* years 1996 and 2008.[48] The rationale is that

[47] Classic statistical inference may be misleading because of small-sample problems, the absence of randomization designs and/or probabilistic sampling methods to select sample units.

[48] Another potential concern for the identification strategy stems from the timing of the treatment

in 1996 the treated region, Genoa, should not be affected by the IIT, while in 2008 one would expect to find anticipatory effects. Therefore, any discovered impact of IIT with such specifications should be suspicious, casting some doubts on the effects found in previous analysis.

Figure 7 shows results for the *fake* implementation year 1996 in left panels, while those for the *fake* implementation year 2008 are presented in right panels. Bottom panels rely instead on the sub-sample in which all patents that refer to the IIT have been identified and dropped. Reassuringly, no direct effects of IIT's *fake* implementation year 1996 on the innovative capacity of the treated region is detected; moreover, by analysing results from right panels, one can clearly observe important anticipatory effects, as expected, thus corroborating the validity of the research design.

Second, following Abadie & Gardeazabal (2003) and Abadie et al. (2010, 2015), "in-space" permutation placebo tests are also proposed. In particular, the latter involves an artificial redistribution of the treatment to regions not exposed to the intervention: therefore, in every reiteration of the SCM one estimates placebo impacts for every potential control region, achieving a distribution of placebo effects.[49] The rationale is to reassess the pseudo-effect of IIT on untreated regions compared to the actual effect on Genoa. Indeed, the level of confidence that the intervention has led to an effect on the outcome of interest for the treated region would be undermined if the magnitude of the estimated impact fell well inside the core of the distribution of placebo effects.[50] If this is the case, one may argue that synthetic controls do not provide good predictions of the trajectory of the outcome (Abadie et al. 2015).

For reasons of graphical representation, following the approach adopted in Bronzini et al. (2020), the placebo study is restricted to the largest 27 regions (those endowed of an average population above 570284 inhabitants).[51] Results of this test are presented in Figure 8 (left panels). Black lines show estimated gaps between the outcome of interest for Genoa and its synthetic control, while grey lines represent the same gap related with each iteration of the placebo test. As usual, the sub-sample on which the bottom left panel is relying does not includes patents directly filed by IIT.

According to results in left panels of Figure 8, the estimated outcome difference for Genoa during the 2006–2015 post-implementation period seems to be abnormally large with respect to the distribution of placebo gaps for almost all variables in the entire post-treatment period.

In order to confirm results of such permutation test and to assess the statistical significance of paper's findings at conventional confidence levels, an additional permutation placebo test is executed. In particular, the Root Mean Square Predictor Error (RMSPE), before and after the treatment, is considered in order to perform a post/pre-IIT RMSPE test. The rationale is that, although large gaps in the 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 SCM is unable to closely imitate the outcome path before the treatment. Therefore, a wide post-2006 RMSPE does not represent a significant impact of IIT if the pre-2006 RMSPE is also large.

Figure 8 (right panels) shows the ratios between the post-2006 RMSPE and the pre-2006 RMSPE for Genoa (darker bar) and for the other 26 major regions considered in the placebo analysis. Genoa clearly stands out both when considering the full sample (top right panel) and the sub-sample (bottom right panel). These ratios for Genoa are unusually larger than those obtained for the other 26 largest

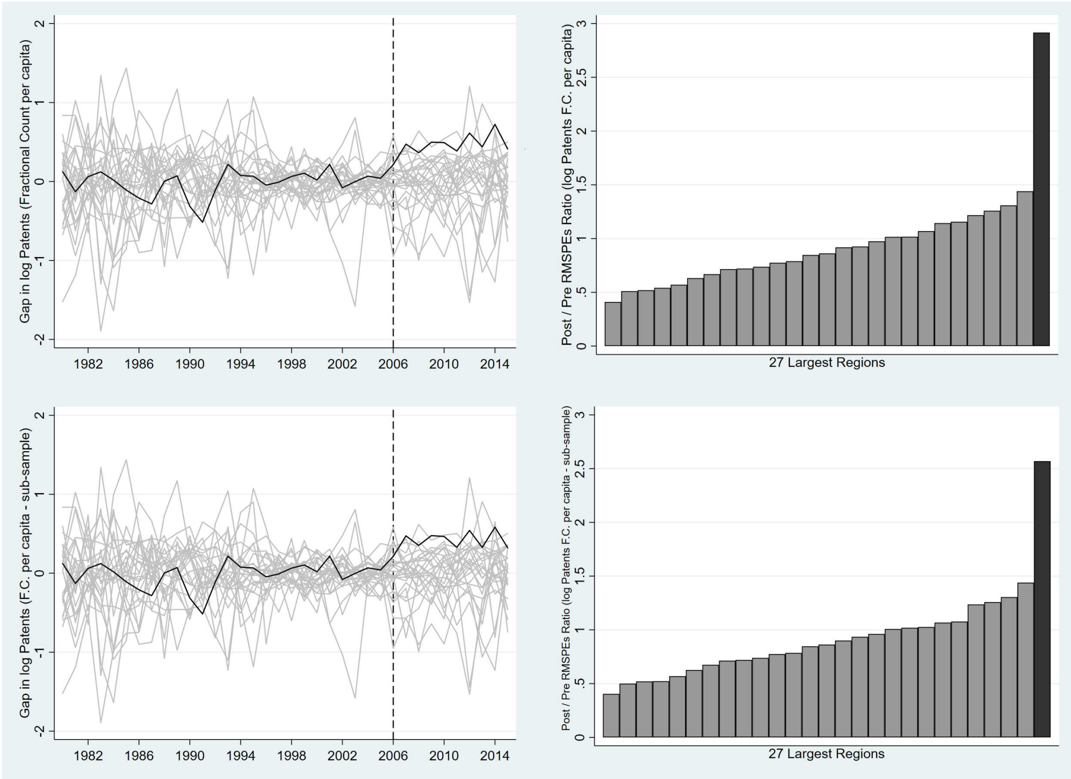
impact, namely the possibility of some anticipation effects. The analysis deals with this concern by relying on such placebo test.

[49]Such process allows to obtain synthetic control estimates for territories not hosting the IIT, assessing the distribution of the test statistic under the null hypothesis of no treatment effect.

[50]More generally, this inferential tool scrutinises whether or not the estimated impact of the IIT implementation is large with respect to the effects distribution for regions not exposed to the intervention. Under the null hypothesis of no intervention effect, the estimated impact of the intervention is then not expected to be abnormal with respect to the distribution of the placebo effects.

[51]The choice of such threshold is based on the regional average population over the sampling period.

Figure 8: Effect of the Location of IIT in 2006. Innovative Capacity. Permutation Placebo Test.



Notes: Inference. Left panels provide inference analysis for the SCM approach, showing permutation placebo gaps, namely the differences between the outcome in the treated (placebo) regions and in the corresponding synthetic ones. Inference considers Genoa (the black line) and 26 regions (those endowed of an average population above 570284 inhabitants) as placebo. Right panels provide Post/Pre IIT RMSPEs tests. The latter refer to Ratios between RMSPEs after and before 2006 for each treated (placebo) unit. Genoa (the darker bar) and remaining 26 regions (those with an average population above 570284 inhabitants) as placebo. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. Sub-sample: all patents that refer to the IIT have been identified and dropped from the analysis.

regions in the placebo study; indeed, by picking one of the 27 largest regions at random from the placebo study, the probability of getting a ratio as high as this would be 1/27 = 0.037. Therefore, it is worth noting that the impact of IIT on the regional innovative capacity is positive and statistically significant at the 5% level.

5.3 Other Outcomes

Following Bonander et al. (2016), the paper investigates whether the creation of IIT in 2006 has influenced other economic outcomes, i.e. the endowment of highly specialised human capital in research (proxied by the number of local inventors per-capita) or per-capita GDP.

The number of inventors residing in the region is indeed well suited to be a proxy for the regional human capital and knowledge base; it is also a fundamental intermediate entrepreneurial outcome which likely affects innovation and local technological development. Further, per-capita regionl GDP is considered with the aim to explore the link between IIT presence and local economic growth.

As in Section 5.1, some preliminary evidence is first provided by implementing a DiD model, as Table 7 shows. 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. Once

Table 7: DiD Estimates. Impact on Research Competences and GDP.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	*Inventors per-capita*				*GDP per-capita*	
$Genoa * Post_{2006}$	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	SUB-SAMPLE	SUB-SAMPLE	FULL	FULL
IIT Own Patents	✓	✓	✗	✗	✓	✓
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 traditional DiD model with panel data, built like $Y_{i,t} = \alpha_i + \beta(Treated_{i,t} * Post_{i,t}) + \mu_i + \tau_t + \epsilon_{i,t}$. 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, β, 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 sub-sample does not include IIT own patents and 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 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

again, the sub-sample does not include IIT own patents and 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).

Results indicate that the implementation of IIT has triggered a rise in the endowment of highly specialised human capital (about 44.78%, or 31.65% considering the sub-sample); moreover, the estimated effects in columns (5) and (6) suggest a significant positive impact also on regional economic performances (9.42%). It is worth stressing that such estimates should be interpreted with caution, in an exploratory data analysis perspective, due to well-known identification threats affecting the DiD method applied to a single treated unit.

Therefore, we tackle the latter by relying on the SCM. In the top panel of Figure 9 results for research competences are shown, while the ones for per-capita GDP are depicted in the bottom panel. Region weights and predictor balance are reported in Table 8.[52] Finally, Table 9 contains the detail of results.

Considering the highly specialised human capital endowment, as shown in Figure 9, the "synthetic Genoa" closely matches the real one in almost all pre-intervention period: in the treated area, after 2006, an increase in the number of inventors is clearly highlighted. In particular, the synthetic Genoa 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 9). 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 scientist.

Turning to per-capita GDP, the synthetic control sensibly replicates the real Genoa in the whole pre-

[52]It should then be noticed that, as explained in previous sections, the synthetic Genoa has been developed as a convex combination of regions in the donor pool that closely imitate the treated unit in terms of pre-intervention values of outcome predictors.

Table 8: Effect of the Location of IIT in 2006. Impact on Research Competences and GDP. Predictor Balance and Region Weights.

Region	Weight	Predictor 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
Napoli	.179	Inventors (million inhabitants 1990)	45.20	45.70
Roma	.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	Predictor Balance	Treated	Synthetic
Alessandria	.037	GDP (per capita 1980-2006 mean)	24554.15	24550.20
Belluno	.052	GDP (per-capita 1980)	17971.91	17968.48
Catanzaro	.054	GDP (per-capita 1985)	20464.66	20459.81
Forlì-Cesena	.152	GDP (per-capita 1990)	23819.68	23818.01
Pescara	.276	GDP (per-capita 1995)	26610.72	26574.63
Savona	.371	GDP (per-capita 2000)	28258.93	28275.95
Trieste	.058	GDP (per-capita 2005)	29650.52	29629.69

Notes: The table shows predictor balance and region weights 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. The set of pre-treatment control variables refers to the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005), as well as the number of active researchers in the region (only for research competences).

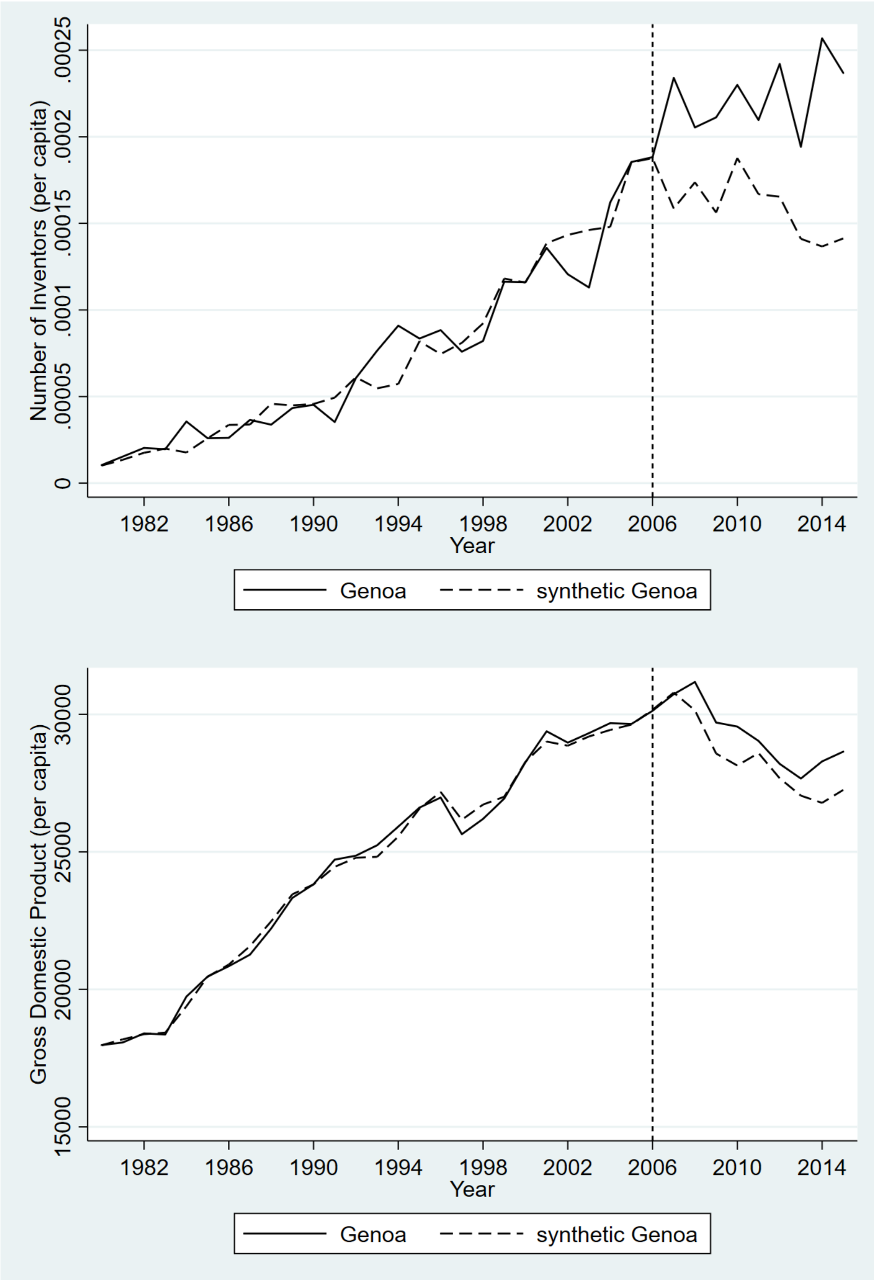
treatment period, as the bottom panel in Figure 9 confirms. If one believes in the goodness of fit among the synthetic control and Genoa during the period prior the intervention, estimates show evidence for a small but meaningful lagged impact of the IIT presence on local GDP per-capita (3.12% per year on average).[53]

These results 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.
In particular, overall economic results seem to be aligned to Liu (2015)'s ones, who highlights a 7% effect on manufacturing per worker from US land-grant universities in the 1860s. In addition, effect estimates also agree with those observed in Valero & Van Reenen (2019), where increases in university presence are positively associated with faster subsequent economic growth. In particular, findings are likely to support 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. It is worth noting that public funded R&D may also increase economic performances in neighbouring regions. Indeed, it is conceivable that the implementation of the IIT may have had economic effects on regions that are spatially close to Genoa, resulting in a spatial reorganisation of economic activities rather than a direct impact of the treatment. However, it should be noticed that other neighbouring regions, except Savona, are not considered in the construction of the synthetic control: this alleviates such potential source of bias.

The location of the IIT has undoubtedly attracted a significant amount of highly-skilled human capital into the hosting region, as previously estimated. This may have led to a prominent process of knowledge accumulation and agglomeration economies in the latter.
As in Section 5.2, by applying the SCM on the sub-sample in which all patents and inventors that refer to the IIT have not been considered, one may disentangle between innovators directly employed

[53]The lag in the impact appears plausible and is likely to be due to the timing of the treatment. Obviously, the implementation of IIT took some time before producing its effects on GDP.

Figure 9: Effect of the Location of IIT in 2006. Impact on Research Competences and GDP. SCM.



Notes: Research competences (Inventors per-capita, in the top panel) and GDP per-capita (in the bottom panel) of the treated region (Genoa) and its synthetic counterfactual. The specification shown in the top panel includes the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005) as well as the number of active researchers in the region. Specification in the bottom panel includes the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005). A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. The weights used to build the synthetic control and predictor balance are reported in Table 8.

in IIT's activities and those referring to private firms and other institutions, thus allowing a better analysis of agglomeration effects. Figure 10 and Table 10 provide results of such exercise.[54]

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

Table 9: Effect of the Location of IIT in 2006. Impact on Research Competences and GDP. 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	1031.90	3.37%
2009	29 703.49	28 576.60	1126.90	3.87%
2010	29 557.11	28 139.01	1418.10	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	1508.74	5.48%
2015	28 645.48	27 252.68	1392.80	4.98%

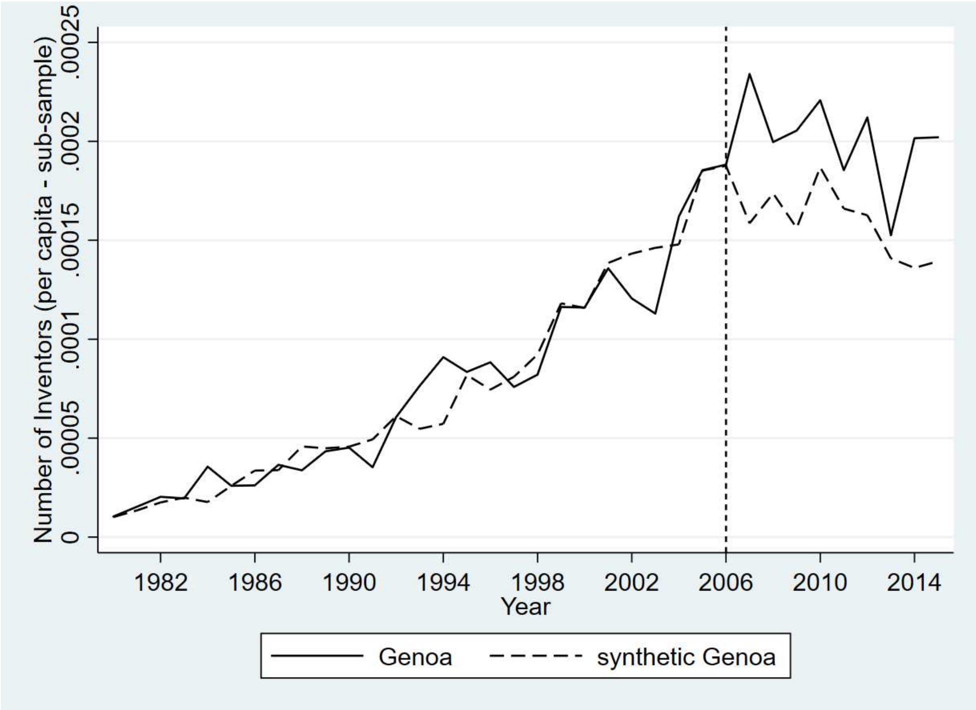
Notes: Research competences (Inventors per-capita, in the top panel) and GDP per-capita (in the bottom panel) of the treated region (Genoa) and its synthetic counterfactual. The specification shown in the top panel includes the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005) as well as the number of active researchers in the region. Specification in the bottom panel includes the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005). A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. 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.

The analysis 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. In particular, 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. Indeed, public funded activities conducted by IIT may make local private firms more productive because of knowledge spillovers (Griliches 1992, Moretti 2004*a*,*b*) and agglomeration economies in the form of localized increasing returns to scale (Greenstone et al. 2010). 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.

Finally, as in Section 5.3, a variety of robustness checks are provided. In particular, usual sensitivity checks on the exclusion of certain regions from the donor pool, as well as "in-time placebos" and "in-space placebos", are proposed.

First, Figure 11 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

Figure 10: Effect of the Location of IIT in 2006. Impact on Research Competences. Sub-Sample.



Notes: Research competences (Inventors per-capita) of the treated region (Genoa) and its synthetic counterfactual. The specification includes the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005) as well as the number of active researchers in the region. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. The weights used to build the synthetic control and predictor balance, not reported, are are available on request. Sub-sample: all patents that refer to the IIT have been identified and dropped from the analysis.

Table 10: Effect of the Location of IIT in 2006. Impact on Research Competences. Sub-Sample. 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	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. The specification includes the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005) as well as the number of active researchers in the region. A one has been added to all patent and inventor count variables before taking the log to include observations with values of zero. 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. Sub-sample: all patents that refer to the IIT have been identified and dropped from the analysis.

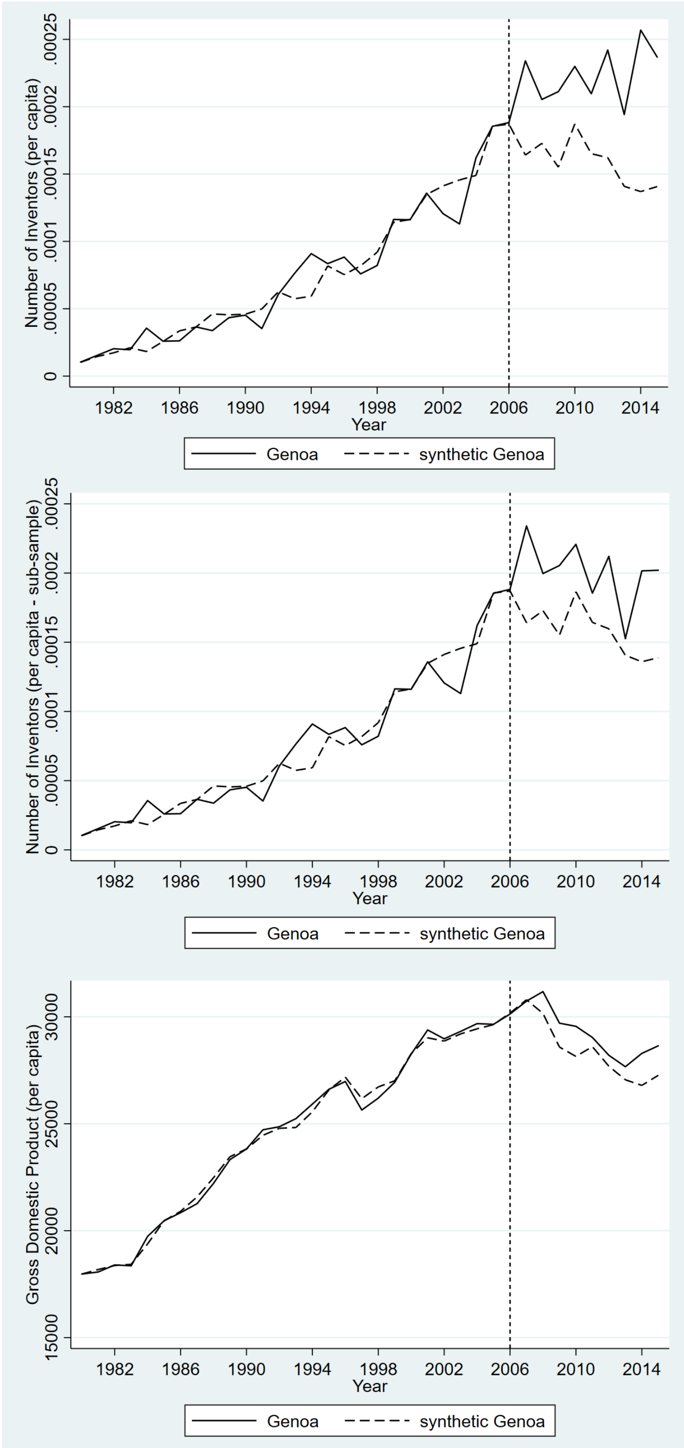
specific economic performance of a single region.[55]
Results from the treated region (Genoa) and its synthetic counterfactual for research competences (Inventors per-capita) are provided in the top panel, while those for GDP per-capita are shown in the bottom one. Again, reassuringly, in both panels outcome patterns are qualitatively and quantitatively similar to those in the baseline specification.

Second, "in-time placebos" tests are performed, as Figure 12 shows. 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 12 is the absence of any impact of IIT on outcomes of interest after the *fake* implementation year 1996 (left panels), while in right panels (*fake* year 2008) significant anticipatory effects are detected, thus corroborating the validity of the research design.

Third, usual "in-space placebo" inference is performed in Figure 13. Again, 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 effect for Genoa is unusually large with respect to the distribution of placebo effects.
Estimated impacts of artificial treatments are depicted in Figure 13. First two top panels 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 purpose. 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 economic performances 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/pre IIT ratios in the bottom-right panel is somewhat weaker. 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. 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.

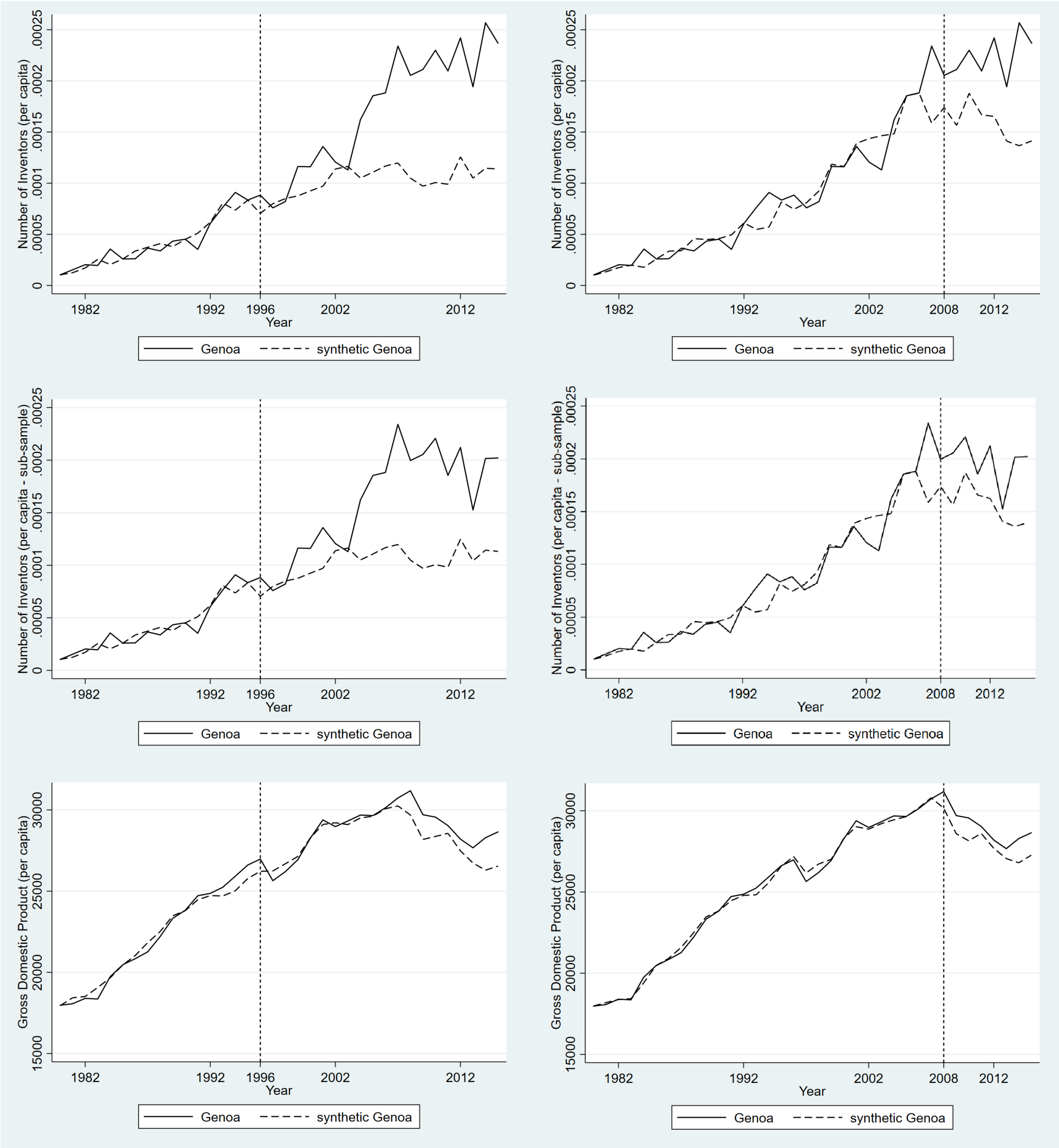
[55] Effect estimates, predictor balance and weighting matrix, not reported, are available on request.

Figure 11: Effect of the Location of IIT in 2006. Impact on Research Competences and GDP. Robustness.



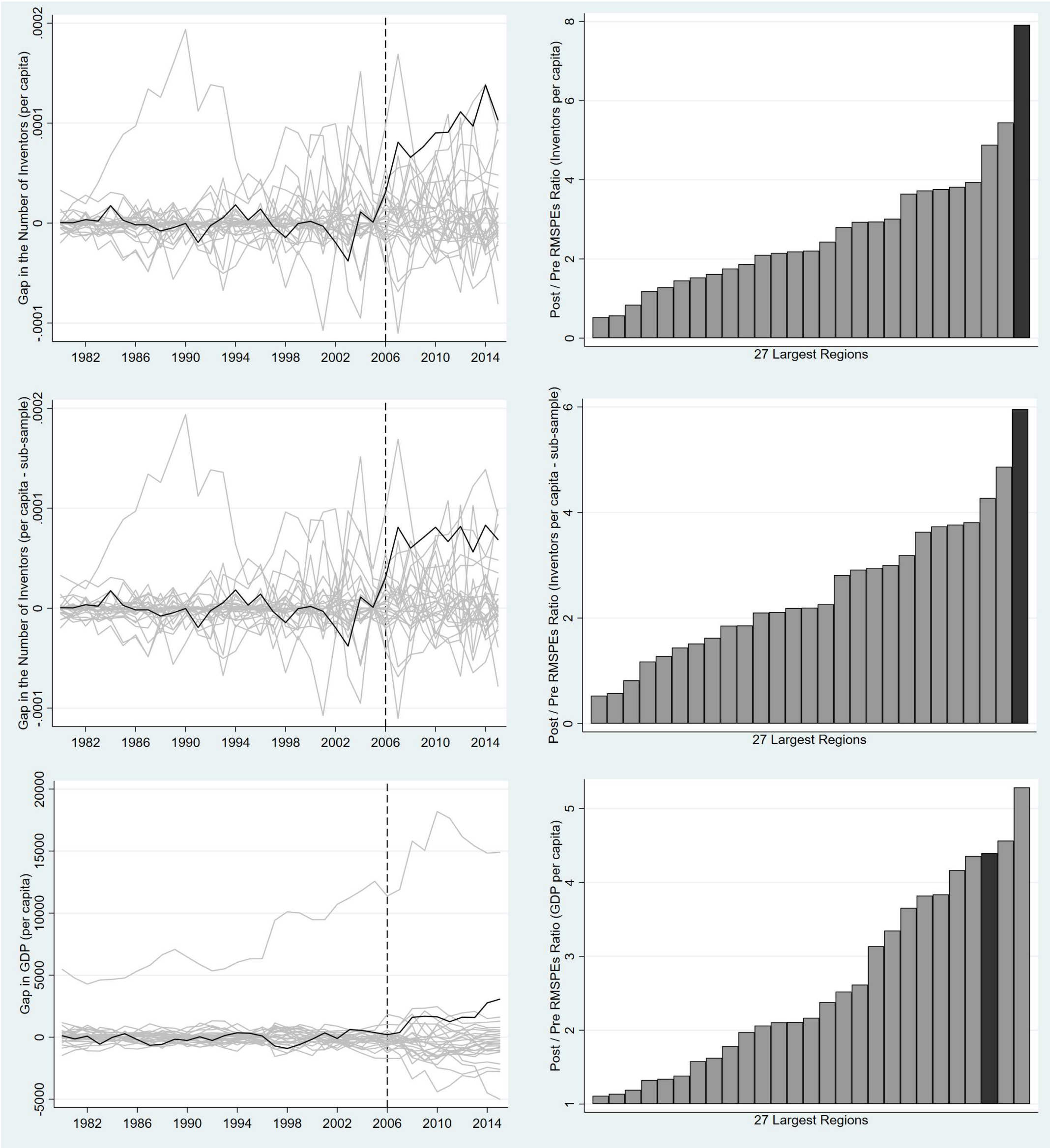
Notes: Research competences (Inventors per-capita, in the top panel) and GDP per-capita (in the bottom panel) of the treated region (Genoa) and its synthetic counterfactual. Sub-sample: all patents and inventors that refer to the IIT have been identified and dropped from the analysis. The specification shown in the first two panels includes the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005) as well as the number of active researchers in the region. Specification in the bottom panel includes the overall mean and several lags of the outcome variable (six lags, from 1980 until 2005). Synthetic Genoa built using a specification that excludes regions where the major four IIT research sites are located, namely 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. The predictor balance and weighting matrix, not reported, are available on request.

Figure 12: Effect of the Location of IIT in *Fake* Years. Impact on Research Competences and GDP. Falsification Test.



Notes: Research competences (Inventors per-capita, in the top panel) and GDP per-capita (in the bottom panel) of the treated region (Genoa) and its synthetic counterfactual. Sub-sample: all patents and inventors that refer to the 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 the left panel *fake* implementation year 1996 is presented. In the right panel *fake* implementation year 2008 is presented.

Figure 13: Effect of the Location of IIT in 2006. Impact on Research Competences and GDP. Permutation Placebo Test.



Notes: Inference. Left panels provide inference analysis for the SCM approach, showing permutation placebo gaps, namely the differences between the outcome in the treated (placebo) regions and in the corresponding synthetic ones. Inference considers Genoa (the black line) and 27 regions (those endowed of an average population above 570284 inhabitants) as placebo. Right panels provide Post/PreIIT RMSPEs tests. The latter refer to Ratios between RMSPEs after and before 2006 for each treated (placebo) unit. Genoa (the darker bar) and remaining 26 regions (those with an average population above 570284 inhabitants) as placebo. The first two panels refer to Research competences (Inventors per-capita), while the bottom panel refers to GDP per-capita. Sub-sample: all patents and inventors that refer to the 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.

6 Conclusions

This work adds on the existing innovation and regional economics literature by relying on the institution of Italian Institute of Technology (IIT), a public funded research centre located in Genoa since 2006, as a probably exogenous policy change that allows to identify the causal effect of public funded research centres on regional innovation and growth. To address this study, the Synthetic Control Method (SCM) is exploited in order to analyse the regional innovative capacity in 1980-2015 period, using patents per-capita as a proxy. Moreover, the impact of IIT on research competences and economic performances, proxied by the number of local inventors and per-capita GDP, are also scrutinized over a period of 10 years after the treatment.

According to estimates, the impact of IIT on the innovative capacity of Genoa is positive and significant; indeed, the treatment has an impact, on average, of about 22.5 more patents per million inhabitants every year (24.37% higher with respect to the synthetic Genoa). Moreover, the paper suggests significant (local) knowledge spillovers from IIT to neighbouring firms. Turning to research competences (in terms of high-skilled human capital), strong evidence that the intervention has triggered a rise in the number of innovators is found. Indeed, Genoa shows on average about 66 more inventors per million inhabitants every year than the synthetic one, with an average relative annual difference of 34%, thus suggesting agglomeration economies. Finally, GDP per-capita is also positively affected by the location of the IIT in 2006. It is worth noting that paper's findings are robust to a variety of robustness and falsification tests, as well as to sensitivity checks.

Overall results are aligned to arguments in Goldstein et al. (1995) and Drucker & Goldstein (2007). Moreover, estimates concur with those of Liu (2015), who highlights a 7% effect on manufacturing per worker from land-grant universities in the US in the 1860s. Improvements in local innovation activity, induced by high quality scientific research from new research centres, are confirmed also in Cowan & Zinovyeva (2013), and Valero & Van Reenen (2019). Moreover, the idea that public funded R&D "crowds in" rather than "crowds out" firm innovation and patent activity is also supported (Moretti et al. 2019). In addition, the effects on research competences and economic growth seem to be aligned with those observed in Valero & Van Reenen (2019).

Finally, it should be noted that public research funding involves policy implications that are not straightforward. Indeed, the assessment of the social return of public research is essential to justify its funding. In particular, given the considerable public funding, R&D activities should deliver a significant stream of private and social returns, in terms of innovation and also economic growth, by attracting high quality researchers, PhD students and star scientists, those that larger benefit productivity and that uniquely have positive long-lasting effects on knowledge accumulation and knowledge spillovers, as suggested also in Waldinger (2016). Consistent with the paper's findings, it is worth noting that the increase in public research funding induced by the IIT presence, as well as the development of human capital and formal skills, have had a significant impact on local economies in the 10 years following the intervention, providing useful insights to inform policy makers about the marginal benefits of additional research funding.

References

Abadie, A., Diamond, A. & Hainmueller, J. (2010), 'Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program', *Journal of the American statistical Association* **105**(490), 493–505.

Abadie, A., Diamond, A. & Hainmueller, J. (2015), 'Comparative politics and the synthetic control method', *American Journal of Political Science* **59**(2), 495–510.

Abadie, A. & Gardeazabal, J. (2003), 'The economic costs of conflict: A case study of the basque country', *American economic review* **93**(1), 113–132.

Abramovsky, L. & Simpson, H. (2011), 'Geographic proximity and firm–university innovation linkages: evidence from great britain', *Journal of economic geography* **11**(6), 949–977.

Acemoglu, D. & Linn, J. (2004), 'Market size in innovation: theory and evidence from the pharmaceutical industry', *The Quarterly journal of economics* **119**(3), 1049–1090.

Adams, J. D. (1990), 'Fundamental stocks of knowledge and productivity growth', *Journal of political economy* **98**(4), 673–702.

Aghion, P., Boustan, L., Hoxby, C. & Vandenbussche, J. (2009), 'The causal impact of education on economic growth: evidence from us', *Brookings papers on economic activity* **1**, 1–73.

Aghion, P. & Howitt, P. (1990), A model of growth through creative destruction, Technical report, National Bureau of Economic Research.

Aghion, P. & Howitt, P. (2005), 'Growth with quality-improving innovations: an integrated framework', *Handbook of economic growth* **1**, 67–110.

Agrawal, A., Galasso, A. & Oettl, A. (2017), 'Roads and innovation', *Review of Economics and Statistics* **99**(3), 417–434.

Amin, A. & Wilkinson, F. (1999), 'Learning, proximity and industrial performance: an introduction', *Cambridge Journal of Economics* **23**(2), 121–125.

Audretsch, D. B. & Feldman, M. P. (1996), 'R&d spillovers and the geography of innovation and production', *The American economic review* **86**(3), 630–640.

Autor, D. H. (2003), 'Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing', *Journal of labor economics* **21**(1), 1–42.

Azoulay, P., Graff Zivin, J. S., Li, D. & Sampat, B. N. (2019), 'Public r&d investments and private-sector patenting: evidence from nih funding rules', *The Review of economic studies* **86**(1), 117–152.

Baldwin, R. E. & Martin, P. (2004), Agglomeration and regional growth, *in* 'Handbook of regional and urban economics', Vol. 4, Elsevier, pp. 2671–2711.

Bankitalia (2016), '100 genova. centenario di palazzo de gaetani sede di genova della banca d'italia', `https://www.bancaditalia.it/chi-siamo/beni-immobili/edifici-storici/palazzo-de-gaetani/centenario_palazzo_de_gaetani_genova.pdf`.

Baptista, R. (1998), 'Clusters, innovation and growth: a survey of the literature', *The dynamics of industrial clusters: international comparisons in computing and biotechnology* pp. 13–51.

Barro, R. & Sala-i Martin, X. (2004), 'Economic growth second edition'.

Beise, M. & Stahl, H. (1999), 'Public research and industrial innovations in germany', *Research policy* **28**(4), 397–422.

Bennett, R. J., Bratton, W. A. & Robson, P. J. A. (2000), 'Business advice: the influence of distance', *Regional Studies* **34**(9), 813–828.

Benoliel, D. & Gishboliner, M. (2014), 'The effect of economic crises on patenting activity across countries', *Chi.-Kent J. Intell. Prop.* **14**, 316.

Black, D. & Henderson, V. (1999), 'A theory of urban growth', *Journal of political economy* **107**(2), 252–284.

Bonander, C., Jakobsson, N., Podestà, F. & Svensson, M. (2016), 'Universities as engines for regional growth? using the synthetic control method to analyze the effects of research universities', *Regional Science and Urban Economics* **60**, 198–207.

Bottasso, A., Conti, M., Robbiano, S. & Santagata, M. (2020), Roads to innovation: evidence from italy, Technical report, University Library of Munich, Germany.

Bronzini, R., Mocetti, S. & Mongardini, M. (2020), 'The economic effects of big events: evidence from the great jubilee 2000 in rome', *Journal of Regional Science* .

Bronzini, R. & Piselli, P. (2016), 'The impact of r&d subsidies on firm innovation', *Research Policy* **45**(2), 442–457.

Cantoni, D. & Yuchtman, N. (2014), 'Medieval universities, legal institutions, and the commercial revolution', *The Quarterly Journal of Economics* **129**(2), 823–887.

Carlino, G. A., Carr, J., Hunt, R. M., Smith, T. E. et al. (2012), The agglomeration of r & d labs, Technical report, Federal Reserve Bank of Philadelphia.

Cohen, W. M. & Levinthal, D. A. (1990), 'Absorptive capacity: A new perspective on learning and innovation', *Administrative science quarterly* pp. 128–152.

Conley, T. G. & Taber, C. R. (2011), 'Inference with "difference in differences" with a small number of policy changes', *The Review of Economics and Statistics* **93**(1), 113–125.

Cowan, R. & Zinovyeva, N. (2013), 'University effects on regional innovation', *Research Policy* **42**(3), 788–800.

Drucker, J. & Goldstein, H. (2007), 'Assessing the regional economic development impacts of universities: A review of current approaches', *International regional science review* **30**(1), 20–46.

Duranton, G., Henderson, V. & Strange, W. (2015), *Handbook of regional and urban economics*, Elsevier.

Eurostat, E. (2013), 'European system of accounts esa 2010', *Official Journal of the European Union* **174**, 56.

Feldman, M. P. (1999), 'The new economics of innovation, spillovers and agglomeration: Areview of empirical studies', *Economics of innovation and new technology* **8**(1-2), 5–25.

Fisher, R., Polt, W., Vonortas, N. S. & Bach, L. (2009), *The impact of publicly funded research on innovation: An analysis of European Framework Programmes for Research and Development*, Office for Official Publications of the European Communities.

Fujita, M. & Thisse, J.-F. (1996), 'Economics of agglomeration', *Journal of the Japanese and international economies* **10**(4), 339–378.

Fujita, M. & Thisse, J.-F. (2002), 'Agglomeration and market interaction', *CEPR Discussion Paper 3362* .

Fujita, M. & Thisse, J.-F. (2003), 'Does geographical agglomeration foster economic growth? and who gains and loses from it?', *The Japanese Economic Review* **54**(2), 121–145.

Goldstein, H. A., Maier, G. & Luger, M. (1995), 'The university as an instrument for economic and business development: Us and european comparisons', *Emerging patterns of social demand and university reform: Through a glass darkly* pp. 105–133.

Greenstone, M., Hornbeck, R. & Moretti, E. (2010), 'Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings', *Journal of Political Economy* **118**(3), 536–598.

Griliches, Z. (1992), 'The search for r&d spillovers', *The Scandinavian Journal of Economics* pp. S29–S47.

Grossman, G. M. & Helpman, E. (1993), *Innovation and growth in the global economy*, MIT press.

Harhoff, D. (2000), Are there financing constraints for r&d and investment in german manufacturing firms?, *in* 'The economics and econometrics of innovation', Springer, pp. 399–434.

Hausman, N. (2012), 'University innovation, local economic growth, and entrepreneurship', *US Census Bureau Center for Economic Studies Paper No. CES-WP-12-10* .

Heckman, J. J. & Hotz, V. J. (1989), 'Choosing among alternative nonexperimental methods for estimating the impact of social programs: The case of manpower training', *Journal of the American statistical Association* **84**(408), 862–874.

Hervas-Oliver, J.-L. & Albors-Garrigos, J. (2009), 'The role of the firm's internal and relational capabilities in clusters: when distance and embeddedness are not enough to explain innovation', *Journal of Economic Geography* **9**(2), 263–283.

Izushi, H. (2003), 'Impact of the length of relationships upon the use of research institutes by smes', *Research policy* **32**(5), 771–788.

Jaffe, A. B. (1989), 'Real effects of academic research', *The American economic review* pp. 957–970.

Jaffe, A. B., Trajtenberg, M. & Henderson, R. (1993), 'Geographic localization of knowledge spillovers as evidenced by patent citations', *the Quarterly journal of Economics* **108**(3), 577–598.

Jones, C. I. (2005), Growth and ideas, *in* 'Handbook of economic growth', Vol. 1, Elsevier, pp. 1063–1111.

Kantor, S. & Whalley, A. (2014), 'Knowledge spillovers from research universities: evidence from endowment value shocks', *Review of Economics and Statistics* **96**(1), 171–188.

King, G. & Zeng, L. (2006), 'The dangers of extreme counterfactuals', *Political Analysis* **14**(2), 131–159.

Kreif, N., Grieve, R., Hangartner, D., Turner, A. J., Nikolova, S. & Sutton, M. (2016), 'Examination of the synthetic control method for evaluating health policies with multiple treated units', *Health economics* **25**(12), 1514–1528.

Lane, P. J. & Lubatkin, M. (1998), 'Relative absorptive capacity and interorganizational learning', *Strategic management journal* **19**(5), 461–477.

Lane, P. J., Salk, J. E. & Lyles, M. A. (2001), 'Absorptive capacity, learning, and performance in international joint ventures', *Strategic management journal* **22**(12), 1139–1161.

Liu, S. (2015), 'Spillovers from universities: Evidence from the land-grant program', *Journal of Urban Economics* **87**, 25–41.

Love, J. H. & Roper, S. (2001), 'Outsourcing in the innovation process: locational and strategic determinants', *Papers in Regional Science* **80**(3), 317–336.

Mansfield, E. & Lee, J.-Y. (1996), 'The modern university: contributor to industrial innovation and recipient of industrial r&d support', *Research policy* **25**(7), 1047–1058.

Minerva, G. A. & Ottaviano, G. I. (2009), 'Endogenous growth theories: Agglomeration benefits and transportation costs', *Handbook of Regional Growth and Development Theories. Edward Elgar, Cheltenham* .

Moretti, E. (2004*a*), 'Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data', *Journal of econometrics* **121**(1-2), 175–212.

Moretti, E. (2004*b*), 'Workers' education, spillovers, and productivity: evidence from plant-level production functions', *American Economic Review* **94**(3), 656–690.

Moretti, E., Steinwender, C. & Van Reenen, J. (2019), The intellectual spoils of war? defense r&d, productivity and international spillovers, Technical report, National Bureau of Economic Research.

Nelson, R. R. (1993), *National innovation systems: a comparative analysis*, Oxford University Press on Demand.

Neumark, D. & Simpson, H. (2015), Place-based policies, *in* 'Handbook of regional and urban economics', Vol. 5, Elsevier, pp. 1197–1287.

OECD (2013), *OECD Compendium of Productivity Indicators 2013*, OECD Publishing.

Pakes, A. & Griliches, Z. (1980), 'Patents and r&d at the firm level: A first report', *Economics letters* **5**(4), 377–381.

Polanyi, M. (2009), *The tacit dimension*, University of Chicago press.

Romer, P. M. (1990), 'Endogenous technological change', *Journal of political Economy* **98**(5, Part 2), S71–S102.

Rosenberg, N. & Landau, R. (1986), *The Positive sum strategy: harnessing technology for economic growth*, National Academies Press.

Rubin, D. B. (2005), 'Causal inference using potential outcomes: Design, modeling, decisions', *Journal of the American Statistical Association* **100**(469), 322–331.

Smith, K. (2005), 'Measuring innovation'.

Toole, A. A. (2012), 'The impact of public basic research on industrial innovation: Evidence from the pharmaceutical industry', *Research Policy* **41**(1), 1–12.

Torre, A. & Gilly, J. (2000), 'Debates and surveys: On the analytical dimension of proximity dynamics" regional studies; apr 2000; 34, 2', *Academic Research Library pg* **169**.

Valero, A. & Van Reenen, J. (2019), 'The economic impact of universities: Evidence from across the globe', *Economics of Education Review* **68**, 53–67.

Waldinger, F. (2016), 'Bombs, brains, and science: The role of human and physical capital for the creation of scientific knowledge', *Review of Economics and Statistics* **98**(5), 811–831.

Zuniga, P., Guellec, D., Dernis, H., Khan, M., Okazaki, T. & Webb, C. (2009), 'Oecd patent statistics manual', *Francia: OECD Publications* .

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.[56] 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.[57]

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.[58] 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 robotics, robotics, brain and cognitive sciences, nanochemistry, nanostructures, nanophysics, pattern analysis and computer vision.[59] In addition, IIT is present in several remote centres, where scientists collaborate with researchers at the university hosting the centre, chasing conjoint scientific aims for the Institute and the university.[60]
IIT currently employs 1716 people, of which about 80% is attributable to the scientific area, and it is characterized by an high level of internationalization.[61] 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%

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

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

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

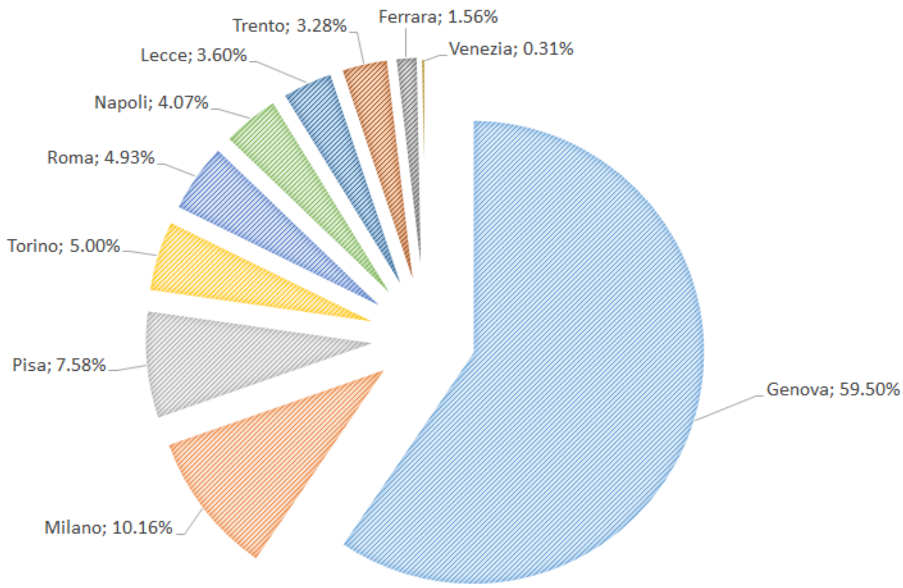
[59] IIT also has several joint technology laboratories with companies and public institutes.

[60] 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 Milano; the Centre for Genomic Science in collaboration with European School of Molecular Medicine in Milano; 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 Roma; 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.

[61] See `https://www.iit.it/it/istituto`.

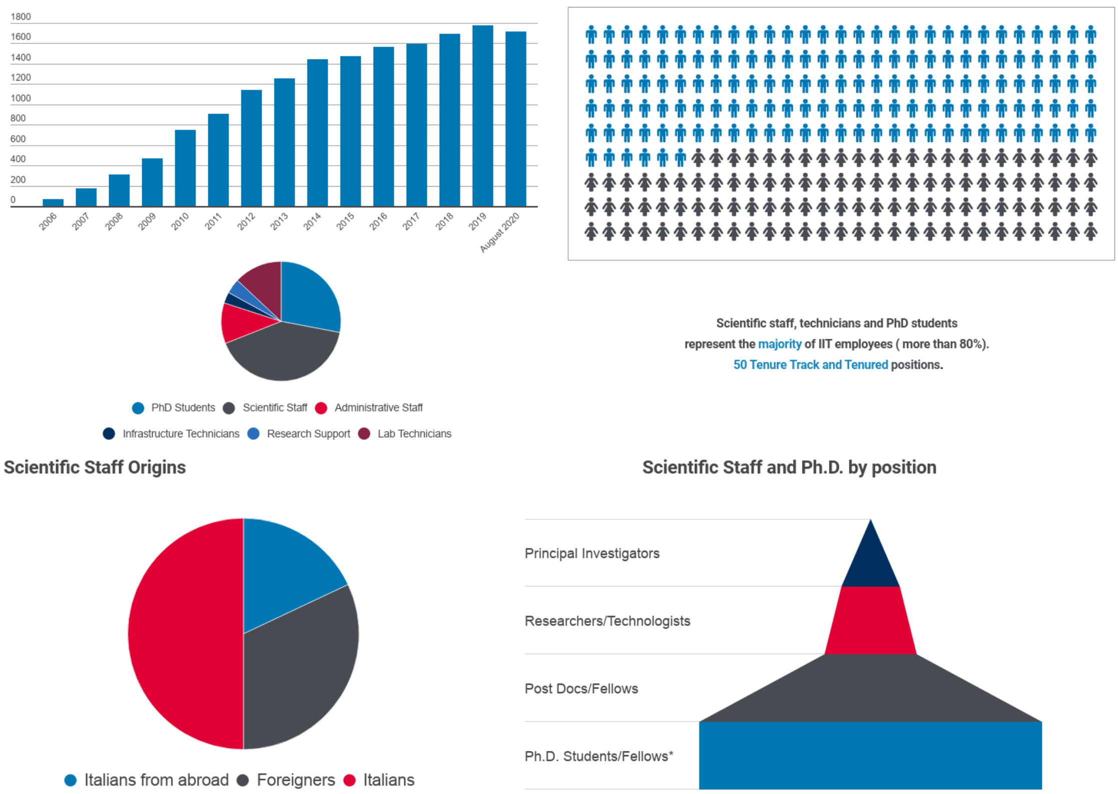
Ph.D. students and recipients of scholarships, with an average age of 36 years. Figures A.1 and A.2 show the IIT human capital endowment.[62]

Figure A.1: IIT Human Resources Endowment for Research by Location.



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

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



Source: Author's elaboration from `https://iit.it/about-us/institute`.

Research activities follow a specific strategic plan (currently based on 2018-2023 time-period and

[62]Data updated to December 2020.

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).

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.

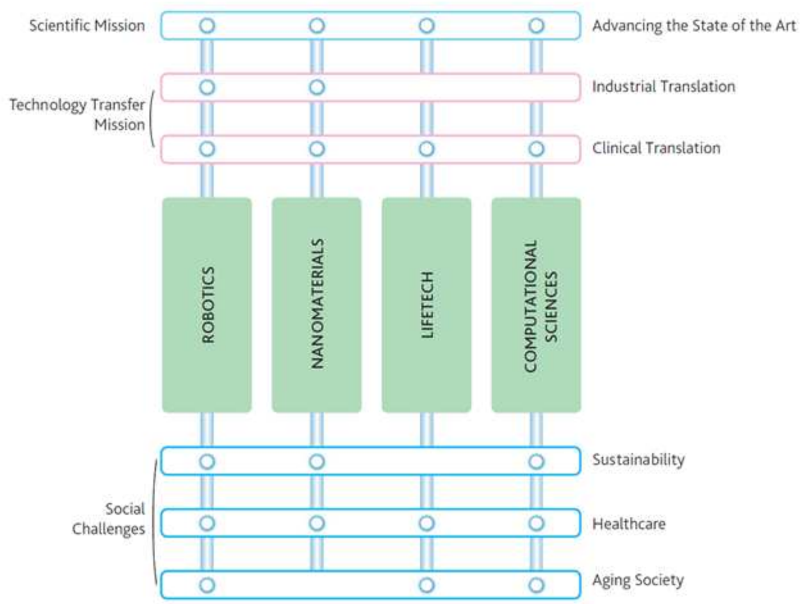
II Nanomaterials domain focuses with new sustainable and or biodegradable materials, nano-composites, 2D materials, nano-fabrication technologies and nano-devices, and new colloid chemistry approaches. In particular, research activities affect Nanomaterials for Sustainability, Nanomaterials for Energy, 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 Computer Vision.[63]

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.

Figure A.3: IIT Research Organization.



Source: https://www.iit.it/research/domains.

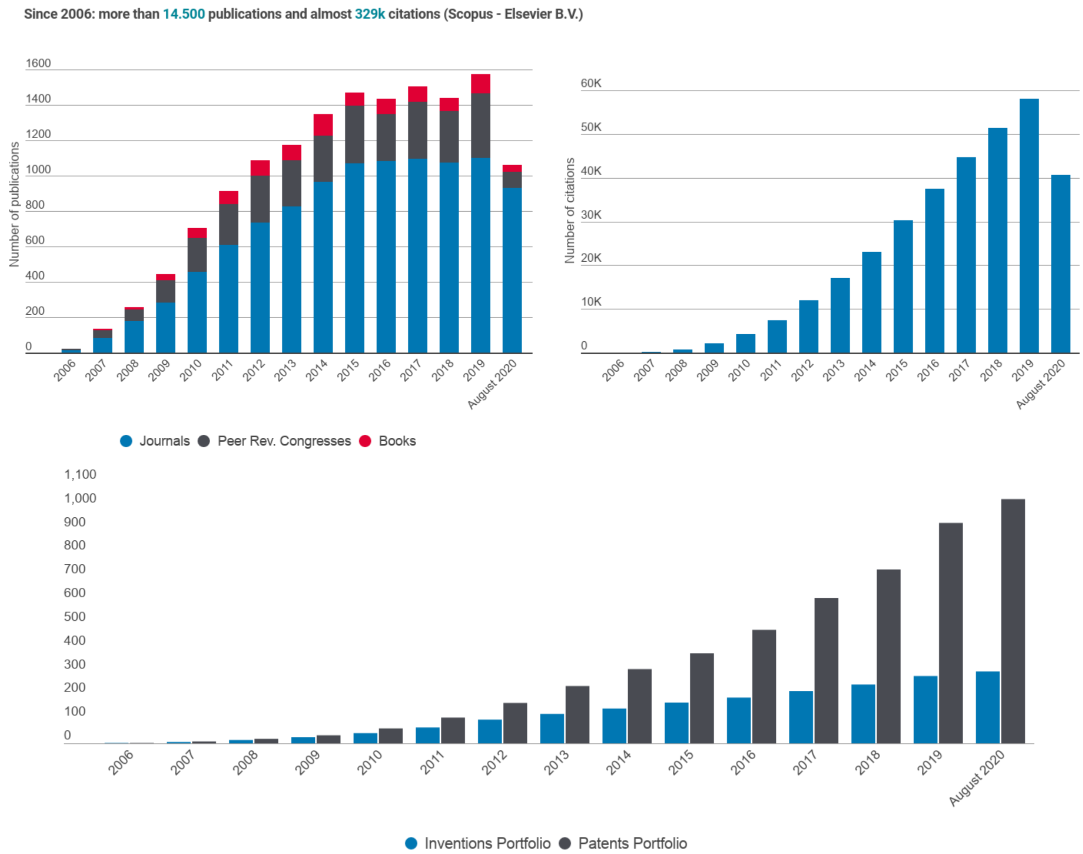
In 2018 IIT has attracted public funding of about €91 million, 80% of which has been allocated to technical-scientific activities. In addition, external funding obtained directly from the Foundation has amounted to €340 millions since 2006, of which 71% from competitive projects, 24% from commercial

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

projects and 5% from in-kind projects.

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, 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.[64]

Figure A.4: IIT Scientific Production.



Source: https://www.iit.it/results/publications-talks.

In particular, from 2006 to 2019, IIT's activities have generated a flow of approximately 14500 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.4).

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