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Smart Electricity Grids in the UK and Italy

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WORKING PAPER

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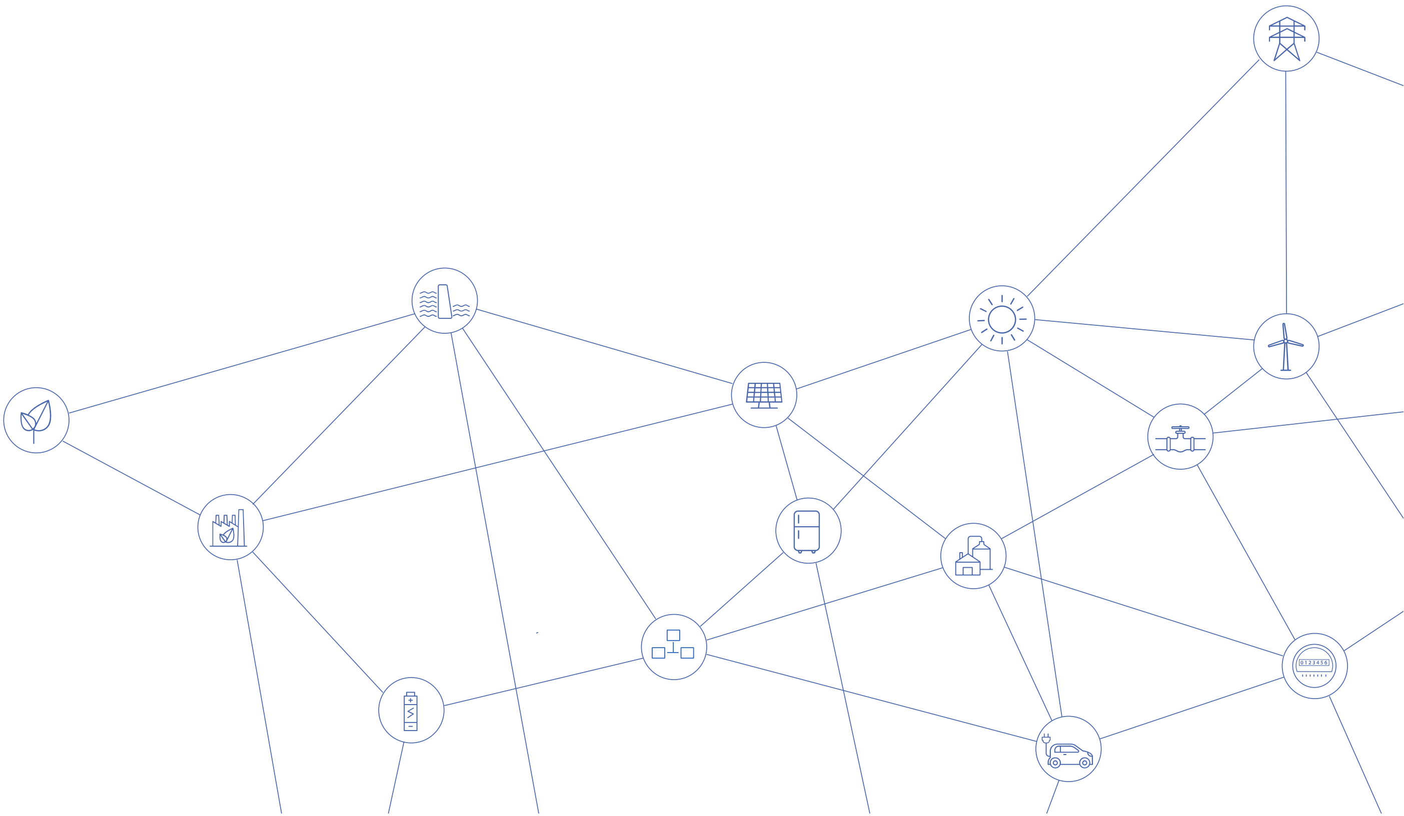

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Beatriz Couto Ribeiro
Tooraj Jamasb

Department of Economics – Porcelænshaven 16A, 1. DK-2000 Frederiksberg

Innovation by Regulation: Smart Electricity Grids in the UK and Italy

Beatriz Couto Ribeiro [a,b], *Tooraj Jamasb* [c]
[a] Technical University of Berlin (TUB) [b] University of Campinas (UNICAMP)
[c] Copenhagen School of Energy Infrastructure (CSEI),
Department of Economics, Copenhagen Business School

Abstract

With the rise of renewable and distributed energy sources, electricity distribution and transmission utilities are facing increasing demand by regulators to innovate and adopt new technologies and transit to smart grids. However, these regulated natural monopolies often lack economic incentives to develop and adopt new technologies. To overcome this barrier, some regulatory authorities have introduced the so-called "innovation-stimuli" regulations to foster experimentation, technological adoption, and innovative solutions. We analyze and compare the effectiveness of two different innovation-stimuli regulations, the cost-pass through and WACC approaches, in the UK and Italy, respectively. To assess the impact of these different regulations on innovation, we use synthetic control (SC) and synthetic difference-in-differences (SDID) methods, which constitute causal inference techniques for small-n case study design and, for the first time, are employed to assess the impact of regulations on innovation outputs. Our panel data encompasses 13 European countries covering 1995 to 2013 and used smart grid projects and patent applications as dependent variables. Differently from what one might expect, not every innovation-stimuli regulation effectively supports innovation outputs. Meanwhile, cost-pass-through significantly and positively affected patent applications in the UK. In Italy, WACC did not affect patent applications, and European Commission-funded projects mostly drove the increases in smart-grid projects.

Keywords: innovation, electricity sector, regulation

JEL: K23, O31, Q48

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[a] Corresponding author. Email: coutoribeiro@campus.tu-berlin.de (Beatriz Couto Ribeiro)

1. Introduction

The electricity sector needs to achieve further decarbonization, decentralization, and flexibility to support the global carbon neutrality target (Connor et al., 2014). To fulfill these requirements, considerable efforts and investments are needed from the electricity utilities (Cambini et al., 2016). Countries have adopted strategies, policies, and regulations to overcome the fossil-fuel lock-in and enable the energy transition (Popp, 2019). Instruments such as price support mechanisms, emissions trading systems, and auctions have been designed to incentivize the transition. These instruments mostly support renewable energy technologies and few were designed to incentivize the much-needed modernization of the grids, a bottleneck in the energy transition (Anaya et al., 2022).

The increasing share of renewable energy challenges the current passive grid structure because of its power variability generated in different periods of the day and decentralized generation (Phuangpornpitak and Tia, 2013). The term "smart grids" applies to a range of technologies, including smart meters and other communication instruments, such as sensors and integration plug-ins to electric vehicles, storage, and renewable energy sources. These technologies are central to enabling the shift from passive to active network management, as they allow for self-healing from power disturbance events, active participation by consumers, offer resilience against physical and cyber-attacks, accommodate diverse generation and storage options and permit the usage of new products, services, and markets; allowing the grid to optimize its assets and operate efficiently (Clastres, 2011).

Given the importance of the smart grids for the energy transition and the slow pace of the electricity utilities in adopting them, some regulatory authorities, especially in Europe, have introduced "innovation-stimuli" regulations to promote electricity grid modernization with a focus on smart grid technologies (Ribeiro et al., 2023). The literature has been restricted to measuring the effect of innovation-stimuli regulations. Cambini et al. (2016) found a positive impact of innovation-stimuli regulations on investment allocation in smart grid, and Ribeiro et al. (2023) demonstrated an aggregated positive effect of innovation-stimuli regulations on patents in European countries.

This paper compares the effectiveness of two stimuli regulations on innovation outputs, particularly the WACC-based approach, and the cost-pass through. To assess the impact of these regulatory models, our research considered two cases of pioneering countries in innovation-stimuli regulation implementation (Cambini et al., 2020). The cost-pass through regulation in the UK and the WACC-based incentive regulation in Italy. We use the synthetic control method (SCM) and the synthetic difference-in-differences

(SDID) methods, which constitute causal inference techniques for small-n case study design, to identify the causal impact of these regulations on patent applications and R&D projects in smart electricity grid technologies.

The contribution of this paper is threefold. First, we analyze the effect of different innovation-stimuli regulation designs on innovation outputs, such as patent applications and smart grid projects. Second, we show that innovation-stimuli regulation cost-pass through is more effective than the WACC approach to support R&D in smart electricity grids. Third, we make novel use of the methodologies synthetic control and synthetic difference-in-difference to evaluate regulatory impact. These methods help solve the challenges related to finding counterfactuals for the effect estimation of regulatory intervention, even with the shortcoming of a small number of unaffected units.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical background of innovation- stimuli regulation. Section 3 presents the conceptual framework and the case of the UK and Italy. Section 4 describes the methodology, the procedure employed for country assignment to treatment and control group, the variables, and the econometric specification. Section 5 presents the results of our synthetic control model, robustness checks, and the treatment effect decomposition. Section 6 discusses the empirical findings. Section 7 concludes and provides policy lessons.

2. Literature Review

The incentives for innovation in electricity grids differ from those in competitive economic sectors. In the non-regulated market, the firms are compensated for costly and risky R&D investments by gaining competitive advantage over other firms. However, this does not hold in regulated networks with no or low competition, small product differentiation, high sunk costs, and remuneration decided by the national regulatory authority (NRA) (Baldwin et al., 2012). Combining these factors provides electricity utilities, the DSOs (Distribution System Operators) and TSO (Transmission System Operators), the regulated segment with low incentives to innovate (Ruttan, 1997).

Consequently, economic incentives have been used in regulated markets as a main tool to enforce the desired behavior of the firms[1]. Studies demonstrated that regulatory approaches, such as cost of service and incentive regulations, guaranteed increased investments in efficiency and profitability; however, they have

[1] The firms' remuneration for the distribution services is determined by the national regulator, responsible for approving the firms' capital and operational expenditures and depreciation to guarantee the investor a fair return on prudent investments (Armstrong and Sappington, 2006).

not incentivized the expansion of R&D investments to integrate new technologies in the grid (Cambini and Rondi, 2010; Abrardi et al., 2018, Marino et al., 2019). Since the liberalization in the 90s, the average rate of innovation in the electricity sector shrunk, especially led by private R&D investments (Nemet and Kammen, 2007; Jamasb and Pollitt, 2011; Sanyal and Ghosh, 2013). According to Nemet and Kammen (2007), in the U.S. from 1980 to 2003, public R&D declined by 54%, private R&D by 67%, and patenting by 47%, and a similar trend was noticed in Europe with a decline of about 70% on R&D expenditure, also in the UK (Jamasb and Pollitt, 2011) and in Italy (Sterlacchini, 2012). The decreasing value added to new technologies in the new electricity sector competition structure, and the fact that R&D investments cannot be recovered from consumers are among the factors that could explain the reduction in innovation activity (Jamasb and Pollitt, 2011; Sterlacchini, 2012; Sanyal and Ghosh, 2013).

To change this downward tendency, the NRAs introduced innovation-stimuli regulations to provide the grid utilities financial incentives to invest in R&D. The innovation-stimuli regulations should minimize the financial and technological risks involving investments in technologies that are not mature and require significant financial resources and new learning capabilities (Cambini et al., 2016). Since the mid-2000s, the innovation-stimuli regulations constituted a regulatory tool used in several European countries to foster research, development, and innovation activities in energy firms (Ribeiro et al., 2023). According to Pollitt (2021), the innovation-stimuli regulations have a more "downstream" policy level since they focus on electricity firms' industry learning through experimenting and introducing innovations[2].

To design them, the regulators suffer a dilemma. On the one hand, the regulators desire firms to undertake risky innovation activities. On the other hand, they disapprove inefficient investment choices and want to avoid providing complete security in covering the expenditures related to these activities since risks associated with such expenditures may be foreseeable and, therefore, can be effectively managed by regulated firms. Under this scenario, regulators aim to design a balanced scheme of incentives and risk sharing by providing higher returns or "risk premium" since innovative investments are harder to recuperate (Pollitt, 2021). Finding this balance is challenging, and as a consequence, many different regulatory designs to support innovation in utilities have emerged (Jamasb et al., 2021).

Jamasb et al. (2021) has categorized four different regulatory methodologies to foster innovation in energy sectors: (i) RAB-based approach; (ii) WACC-based approach; (iii) cost-pass through; (iv) competition-based. The "RAB-based approach" to innovation expenditure involves the research and

[2] The main papers analyzing the impact of regulation in innovation and findings are in Appendix A.

development (R&D) and innovation spending of a firm being included in the Regulatory Asset Base (RAB) of the utility. The WACC-based method differentiates between the capital remuneration for innovative assets and conventional investments of regulated firms to reflect the higher risk associated with innovation investments. In "cost-pass through", R&D and innovation are considered part of the spending that ratepayers finance through network charges or energy prices. Lastly, the "competition-based" mechanisms fund the most highly rated research projects. To evaluate the projects, tenders participate in a competitive bidding process to fund their proposed innovation initiatives.

These regulations constitute new regulatory incentives, and the literature has only marginally examined them[3]. Most studies focused on the European cases and are primarily descriptive and case studies (Vítor Marques et al., 2014; Cambini et al., 2016, 2020; Jamasb et al., 2021). Using statistical analysis, Cambini et al. (2016) showed that innovation-stimulus mechanisms by regulation (e.g., extra WACC or adjusted revenues) successfully promoted smart grid investments, and Ribeiro et al. (2023) found an average positive effect of innovation stimuli regulation in patent applicants in European countries. However, there is still a gap in addressing the specific impact of different types of innovation stimuli-regulation. Therefore, we propose to analyze the pioneering cases of the UK and Italy, which introduced different innovation-stimuli regulations, the cost-pass through, and WACC, respectively (Müller, 2012).

We apply the causal inference method of synthetic control method (SCM) to compare the R&D outputs of both countries. The SCM was considered by Athey and Imbens (2017) as "arguably the most important innovation in the policy evaluation literature in the last 15 years". This method consists of a statistical technique developed for small and medium-sized sample case studies to evaluate the causal impact of a structural transformation on the variable of interest during a specific period. This method is specifically beneficial to studies on energy analyzing the regulatory impact since one of the main limitations is the small number of contractual (Sterlacchini, 2012). Despite its advantages, the SCM is still limited applied. To the best of our knowledge, in the energy innovation literature, only Scheifele et al. (2022), and Fu et al. (2022) applied SCM. On the regulatory impact evaluation, it has not been employed yet. Therefore, our paper introduces a new venue for regulatory studies.

[3] View Appendix A on "Innovation Stimuli Regulation in Electricity".

3. Case Description and Conceptual Framework

3.1. United Kingdom: Innovation with Cost-Pass Through

The innovation-stimuli regulation cost-pass through was first implemented through the Innovation Funding Incentive (IFI) by Ofgem (Office of Gas and Electricity Markets) in 2005 to fund R&D and deploy smart-grids project trials. The IFI focused on the distribution system asset management deployment (Woodman and Baker, 2008) offering support for R&D projects tackling technical aspects (e.g., network design, operation, and maintenance) of distribution networks with the potential to deliver financial, supply quality, environmental, safety value to end consumers. The amount allocated to fund these investments was capped at 0.5% of utilities allowed revenue, in which 80-90% of the project's costs would be passed onto customers. The IFI as estimated to cost £71,24 million, where £57,44 million would be paid by customers, and £13,8 million by other shareholders[4] (Mott MacDonald and BPI, 2004). Jamasb and Pollitt (2011, 2015) demonstrate that the introduction of IFI resulted in a significant increase in network R&D spending and patent applications in the UK.

After the positive results from IFI, Ofgem introduced the Low Carbon Networks Fund (LCNF) as a new follow-up regulation to stimulate grid innovation between 2010-2015 with a budget of £500 million, corresponding to 2.3% of allowed DNOs revenue (Ofgem, 2009; Lockwood, 2016). In the LCNF, a tiered format was used. The Tier 1 funding targeted small-scale projects, and Tier 2 was an annual competitive process to fund a smaller number of large 'flagship' projects. From this amount, the DNOs would provide 10% of the total project cost as a mandatory contribution that could be recovered upon successful project delivery (Frame et al., 2018).

The award of Tier 2 funding included a direct form of competition between the DNOs[5]. Given the large investments, the utilities boards of directors became more interested in these investments and their potential new commercial relationships and opportunities. Another incentive provided by the LCNF was to stimulate cooperation with suppliers, information, and communications technology (ICT) firms, local communities, and universities. Figure 1 details the dates and guidelines for innovation-stimuli regulation introduced in the UK.

[4] Mott MacDonald and BPI (2004) estimated the total costs of IFI on an average of £14,25 million p.a.

[5] Note that RIIO (Revenue = Incentives + Innovation + Outputs) has similar mechanisms to incentive innovation. However, our analysis did not include the RIIO because it falls outside the paper timeframe.

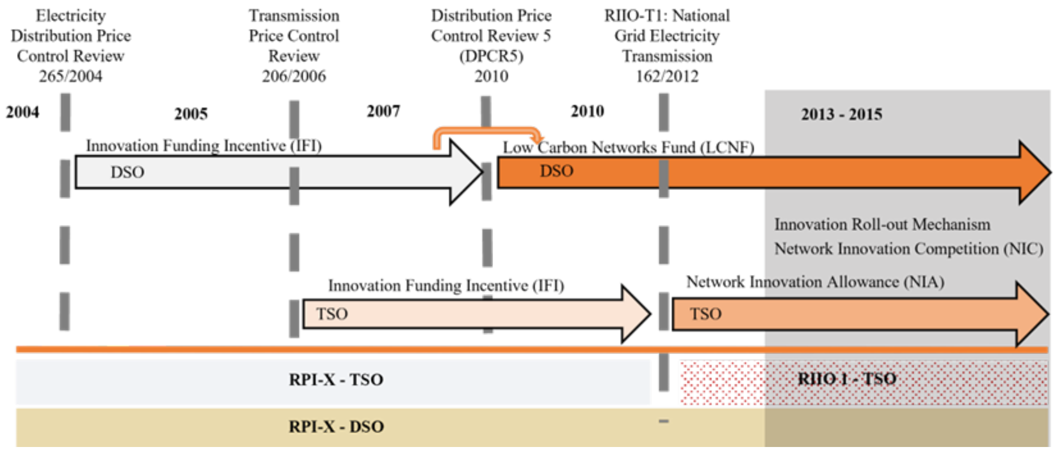

Figure 1: Innovation-Stimuli Regulation Timeline: United Kingdom (Source: Authors)

3.2. Italy: Innovation by Weighted Average Cost of Capital (WACC)

In 2007 in Italy, the NRA Arera (Italian Regulatory Authority) introduced incentives to foster the deployment of smart meters. Electronic meters and related infrastructures were unbundled from the distribution tariff to support the deployment, and specific incentives on OPEX and CAPEX were received. For these investments, ARERA allowed productivity gains (X-factor) was 5.0% for metering and CAPEX with a smart metering specific WACC of 7.2% (Müller, 2012; Lo Schiavo et al., 2013).

In 2010, a WACC mechanism was introduced by Decision 39/2010 (Arera, 2010) to provide stronger incentives to promote innovative smart technologies to integrate all users connected to the grid (generators, consumers, and mixed points). The decision determined that selected demonstration projects would benefit from an extra remuneration of capital cost for 12 years. The regulator and an expert committee would select open and non-proprietary communication projects based on several parameters, including qualitative indicators, technical scores attributed by the experts, and project cost and benefits, as described in Delibera ARG/elt 12/11 (Arera, 2011; Coppo et al., 2015).

The document on ARG/elt 12/11 (Arera, 2011) indicates that 8 projects were selected[6], and their costs were estimated at 16.5 million euros. The selected proposals received an extra-WACC remuneration (+2%) funded through the network tariff. Figure 2 highlights the year and regulatory guidelines that introduced the different innovation-stimuli mechanisms in the electricity sector and its segments in Italy.

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[6] A2A - CP Lambrate, ASM Terni, A2A - CP Gavardo, ACEA Distr., ASSM Tolentino, ENEL Distr. - CP Carpinone, Deval - CP Villeneuve, and A.S.SE.M. San Severino Marche (Arera, 2011).

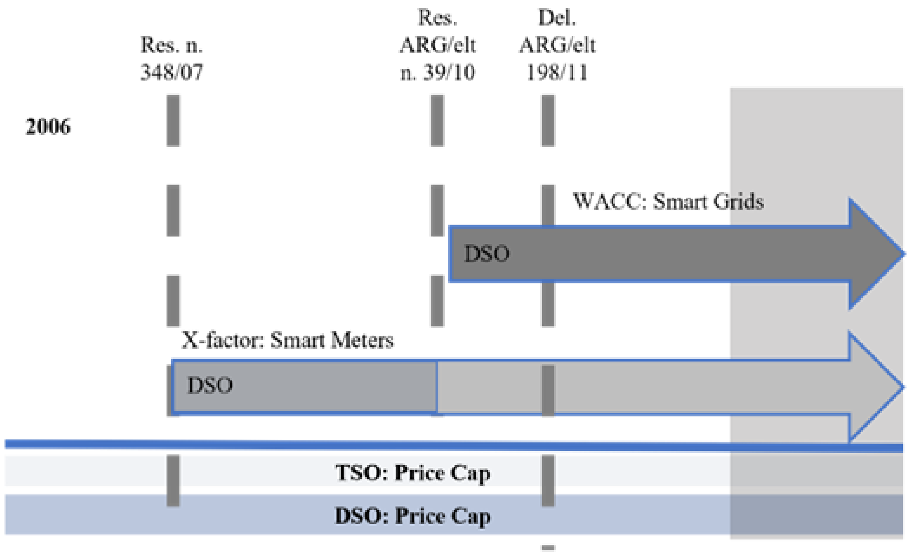

Figure 2: Innovation-Stimuli Regulation Timeline: Italy (Source: Authors)

3.3. Conceptual Framework: Innovation-Stimuli Regulation

We formulate a conceptual framework to elucidate the mechanism behind the cost-pass through and WACC innovation-stimuli regulation approaches. Figure 3 depicts the regulated environment within which utilities are embedded. The top layer describes the regulated environment, including sunk-cost, low competition, and price control, which significantly influences utilities' behavior towards innovation. Among the external factors that interact with the "regulated environment" are the new pressures for the utilities to become more innovative through digitalization, decarbonization, and decentralization. In the second layer, we find the main regulatory mechanisms that determine the firms' remuneration, either through incentive or cost of service regulation. Below each mechanism, the method used to establish utility price and their advantages is indicated.

Based on this standard regulatory framework, we explore three scenarios that describe how utilities might approach R&D activities and expected innovation outputs. In situations without innovation-stimuli regulations, the expected output in terms of R&D investments is low because the R&D expenditure is not incorporated into the utility's cost base or it does not receive a compatible rate of return on these risky investments (Figure 3, the right pathway). As a result, utilities have low incentives to invest in R&D and tend to adopt incremental technologies with a low degree of novelty and find greater challenges to enhance their productivity and adopt new technologies.

To overcome the above limitations, two strategies have been implemented: (i) cost-pass through and (2) WACC, both aim to support "learning-by-doing" through demonstration and pilot projects, and constitute a key step between laboratory tests and full industrial deployment (Coppo et al., 2015). The experiences gained from these projects lead to their subsequent application and integration in real systems, management and estimation of costs, and parameters and factors that should be considered for economic compensation policy. Despite this commonality, the innovation-stimuli regulation approaches some particularities.

The cost-pass through (the left pathway of Figure 3) the R&D as an expenditure subsidized by the consumer up to 0,5% of utilities allowed revenue. With this amount the utilities would covers a significant share of the total investments (usually around 80-90%, of the R&D project’s 195 costs), fosters cooperation with other stakeholders, and requires a minimum of 10% return on R&D projects. Furthermore, mechanisms were introduced to allow additional R&D investments and earlier project termination if they are proven unviable. Moreover, if unexpected gains occur, utilities are allowed to retain these profits. The expected outputs from cost-pass through include “learning-by-doing”, cooperation, demonstration, and pilot projects, also consider intellectual property (IP) 200 spillovers (Ofgem, 2009).

In contrast, the WACC recognizes R&D as a utility investment. Therefore, to incentivize R&D projects the regulatory authority allows a premium 2% rate of return for 12 years for selected projects. The regulation aims to enable learning-by-doing on smart grid technologies through demonstration and pilot R&D projects by enabling deployment and favoring an open and non-proprietary approach. These also ensure that different components and systems communicate effectively, regardless of their manufacturers, fostering interoperability and flexibility.

Both regulatory mechanisms have the aim of contributing to grid adaptation and resilience through "learning-by-doing". However, they diverge in their approaches to fostering such advancements. The cost-pass-through, as implemented in the UK, stands out for its generous allocation of financial resources, cooperation incentives, higher tolerance to failure, and retention of gains, decreasing the utilities’ risk aversion on these investments. In contrast, Italy’s WACC approach is stricter regarding funding and gains retention, which may not encourage utilities to take advantage of the incentives.

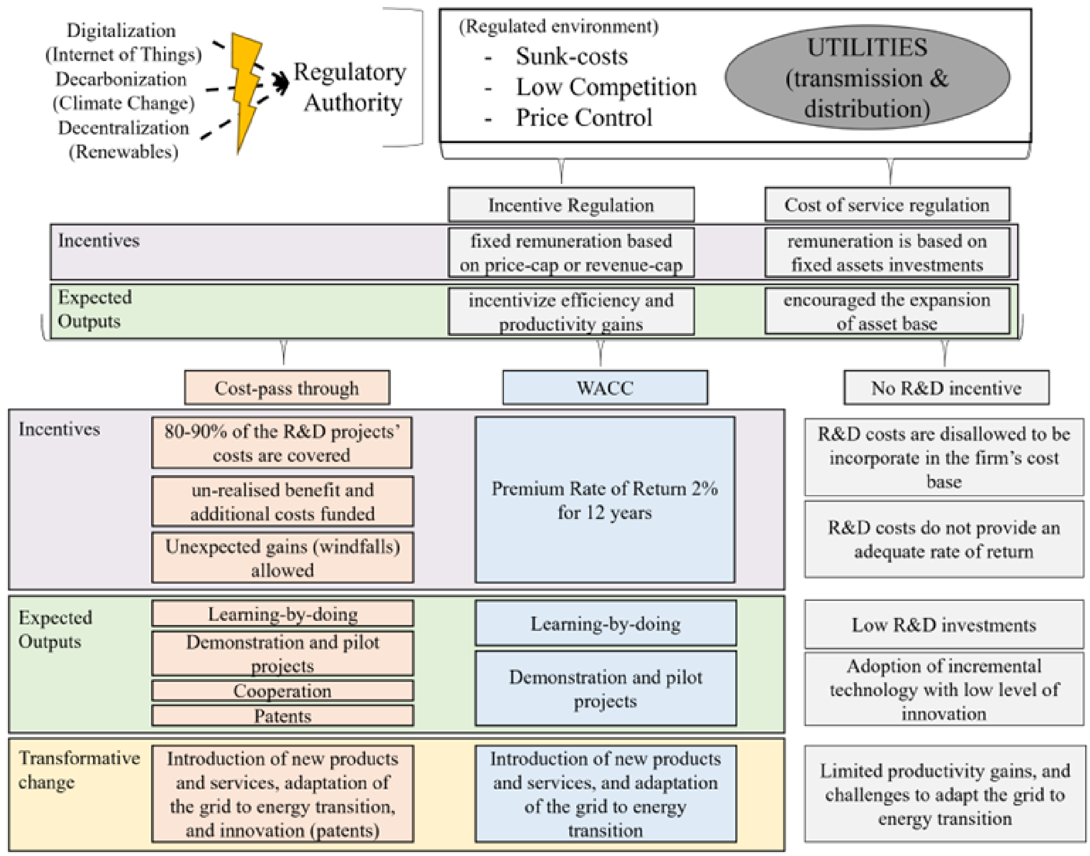

Figure 3: Conceptual Framework: Innovation-Stimuli Regulation. (Source: Authors)

4. Methodology

4.1. Synthetic Control Method

We employ the synthetic control method (SCM) to provide a causal estimation of the policies' impact, mainly used to evaluate small n-case studies (Abadie, 2021). The method is based on a statistical technique to evaluate the causal impact of a structural transformation on the variable of interest during a specific period. The SCM calculates, based on the pool of control units, an optimal weighted control unit — a "synthetic control" — that best reproduces the pre-event (or pre-treatment) behavior of the dependent variable on the unit of interest (Abadie et al., 2015). The central assumption of the SCM is that if there is no economic effect of the structural transformation (the null hypothesis), the variable of interest in the synthetic unit should closely track the real one. If there is an impact, development of the two should be similar before structural transformation, but different after the structural transformation, such as in the difference-in-difference (Castanho Silva, 2018).

The synthetic control is calculated as the weighted average of the units in the donor pool and is represented by a (J × 1) vector of weights W = (w_2,..., w_{j+1}), with $0 \leq wj \leq 1$ for j = 2,... j and w_2,..., w_{j+1} = 1. In these functions, our sample of countries is indexed by J, and j = 1 is our case of interest, and the j = 2 to j = J + 1 is the comparison units (Abadie et al., 2015). The difference between the pre-intervention characteristics of the treated unit and a synthetic control is given by the vector ($X_{1m} - X_{0m}W$). The synthetic control is selected such that the mean squared prediction error (MSPE) of the outcome variable between the treated country and its synthetic control is minimized over the pre-treatment period. To perform that, the SCM chooses the country weights W and the variable weights V for each input variable m:

$$\sum_{m=1}^{\kappa} v_m = (X_{1m} - X_{0m}W)^2 \tag{1}$$

The v_m is a weight that reflects the relative importance assigned to the m-th variable when we measure the discrepancy between X_{1m} and $X_{0m}W$, where W is a vector of weights w between 0 and 1 attributed to each country j that forms part of the synthetic control. The treatment effect is then estimated for the post-treatment periods t (with $t > t_0$), and let Y_{jt} be the outcome of unit j at time t:

$$Y_{1t} = -\sum_{j=2}^{J+1} w_j Y_{jt} \tag{2}$$

We calculated the differences between the post-intervention outcomes in the treated unit and the synthetic control to measure the size of the causal treatment effect (Bonander et al., 2021). We then calculate its time-specific differences for each post-intervention time point t with the equation 3, in which Y_{it} is the time-specific outcome in unit i, in which i = 1 is the treated unit, and others are controls, and w_j^* the unit weight assigned to each control unit by SCM.

$$\widehat{Y_{1t}(0)} = \sum_{i=2}^{N} Y_{it} w_j^* \tag{3}$$

The synthetic control model operates under the stable unit treatment value assumption (SUTVA), assuming no spillover effects on other countries. Based on Ribeiro et al. (2023) innovation-stimuli regulation classification, guaranteeing that the counterfactual in our sample did not have other innovation-stimuli regulation mechanisms until the last year of our timeframe. Moreover, in our SC models, we include the lags of the output variables. The lagged variables operate similar to an "Ashenfelter's dip", which controls for a treatment variable that might be activated in the period preceding the intervention[7]. The synthetic control is built from 13 donor countries[8]. For the UK and Italy, patent application and smart grid projects variable was available between 1995 and 2013. In total, we have four different synthetic control estimations.

As a robustness check, we estimated our models using the synthetic difference-in-differences (SDID) method (Arkhangelsky et al., 2021). The SDID combines SCM and a difference-in-differences (DID) two-way fixed effects estimator. SDID performs well with a small number of treated and control units and provides a robust and efficient method for estimating the treatment effects (Abman and Longbrake, 2023). The SDID relaxes SCM pre-treatment periods because the SDID focuses on pre-treatment periods that are more similar to the treated units and introduces time-specific weights on them to mimic the parallel-trend assumption from the DID. At the same time, SDID allows smaller standard errors than DID because the weights emphasize units and time periods that are more similar to the treated units (Arkhangelsky et al., 2021). The SDID is estimated as follows:

$$\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}, = argmin\left\{\sum_{i=1}^{N}\sum_{t=1}^{N}\left(Y_{i,t} - \mu - \alpha_1 - \beta_1 - W_{i,t}\,\tau\right)^2 \hat{\omega}_i^{sdid}\hat{\lambda}_t^{sdid}\right\} \tag{4}$$

In equation 4, the $Y_{i,t}$ is the outcome variable, τ is the average treatment on the treated, and $W_{i,t}$ refers to the exposure to the binary treatment. Unit and time-fixed effects are represented by (α_i) and (β_t), respectively, which control for unconfoundedness that might affect the country and time averages. The unit weights are $\hat{\omega}_i^{sdid}$ and time weights are $\hat{\lambda}_t^{sdid}$, which respectively refer to the weights used in the matching process of the pre-treatment of unexposed units and the treated ones, and the time weights used to balance pre- and post-intervention period for the control units. Our robustness check estimated the SDID with covariates, and the standard error was estimated using a SCM placebo exercise, which is a suitable approach when there is only one treated unit.

To estimate whether the effects are meaningful, (Arkhangelsky et al., 2021) recommends estimating the τ parameter of the SDID and calculating the sample variance among the different placebo iterations. Therefore, we performed 500 iterations of the placebo exercise for each model to estimate our standard errors.

[7] See Kaul et al. (2022).

[8] We considered the following donor countries: Austria, Belgium, Finland, France, Greece, Hungary, Ireland, Netherlands, Norway, Poland, Slovakia, Spain, and Turkey.

4.2. Data

To measure the effect of innovation-stimuli regulation on innovation efforts in the UK and Italy, we analyse two dependent variables, the number of (a) smart-grid projects and (b) patents applications. The former represents a direct output unit expected by both innovation-stimuli regulations since the relevant NRAs (OFGEM and ARERA), through cost-pass through and WACC, funded pilot or innovative smart-grids projects. The latter constitutes a proxy for innovation level, which despite the convenience in terms of data access, patent applications also convey limitations related to incompatibilities on innovation efforts and the number of patents, and that patenting a technology does not necessarily lead to its subsequent adoption (Popp, 2019).

For smart-grid projects, we used data from the Joint Research Centre (JRC) of the European Commission, responsible for monitoring these projects in the European Union. The JCR smart grids project database comprises information on national and multinational projects in the EU regarding the type of project (R&D or demonstration), stakeholders involved, starting year, program, and funding body supporting the project. The patent data was collected through PAT-STAT maintained by the European Patent Office (EPO). To restrict our research to smart-grids patents, we used the CPC codes suggested by Gregoire-Zawilski and Popp (2022) for the following technologies: (a) systems integration and efficiency (CPC classes Y02E 40/70 and Y04S 10), (b) use in buildings (CPC classes Y02B 70/3* and Y02B 90/2*), (c) ICT applications to smart grids (CPC classes Y04S 40* and Y04S 50*), and (d) end-user applications (Y04S 20)[9]. The unit of analysis is patent families aggregated at the national level in the form of fractional counts based on the residence country of the inventors (de Rassenfosse et al., 2013).

The data consists of balanced panel data from 1995 to 2013. We limited our sample to 2013 in order to distinguish the UK innovation-stimuli regulation policy from subsequent regulatory changes. Our synthetic control models also included four predictors[10]: (i) electricity consumption (GWh); (ii) share of renewables in the electricity grid; (iii) gross domestic product (GDP) per capita; and (iv) country economic complexity index. Electricity consumption was retrieved from the World Bank and accounted for potential differences in the growth of domestic electricity consumption, encouraging the use of smart meters and technologies, and disposition from the utility to invest in R&D in this technology (Giest, 2020; Churchill et al., 2021). Other variables from the Word Bank database are the share of renewables in the electricity grid due to its

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[9] Table B.1 in Appendix B presents the patents code list used in the analysis.
[10] Bonander et al. (2021) and Abadie (2021) affirm that covariates are not strictly required in a synthetic control.

association with smart-grid technology (Connor et al., 2014), and gross domestic product (GDP) per capita, which measures economic prosperity associated with higher budgets to support energy transition investments through the provision of financial resources (Simionescu et al., 2019).

Lastly, we included the country economic complexity index (ECI)[11], retrieved from the Atlas of Economic Complexity. This predictor comprises a proxy for the country-level production structure and economic activities that condition economic growth (Ferraz et al., 2021). We also considered including indicators related to R&D investments; however, the data was not balanced. In addition to the theoretical considerations mentioned, we ran a two-way fixed effect regression to empirically test our predictor variables' significance (Table C.1 in Appendix C presents the regression). Most of the selected variables proved significant, except for the share of renewables in the electricity grid. Nonetheless, we retained this variable in the model because of the strong theoretical link between renewables deployment and the need for smart grid technologies (Connor et al., 2014).

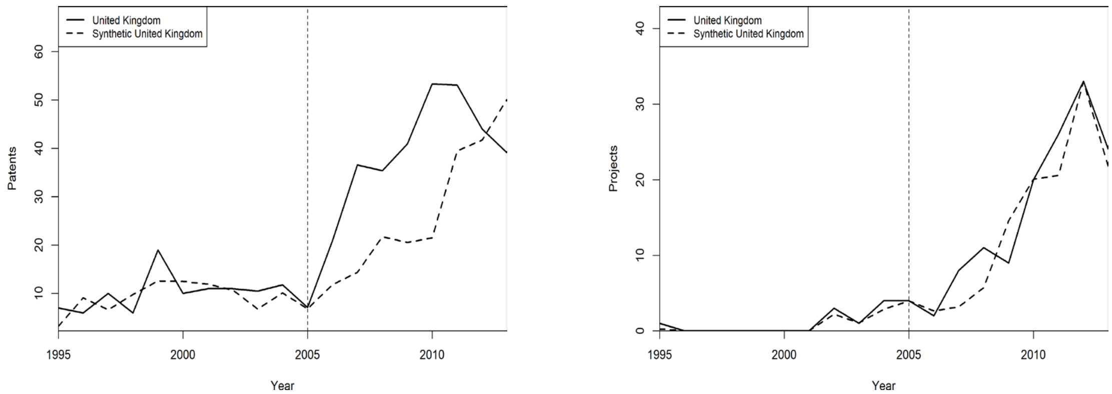
5. Results

5.1 Synthetic Control Analysis

This section assesses the impact of the cost-pass through innovation incentive in the UK and the WACC based incentive in Italy on patent applications and smart-grid projects using the SCM approach. Figures 4 and 5 depict the result of the synthetic control estimation. In the UK, the synthetic control estimating the patents (Figure 4a) shows that after introducing innovation incentives, the number of patents increased beyond those of the counterfactual case. However, there is no significant treatment effect in the case of the number of innovation projects since the trend closely follows the synthetic control (Figure 4b).

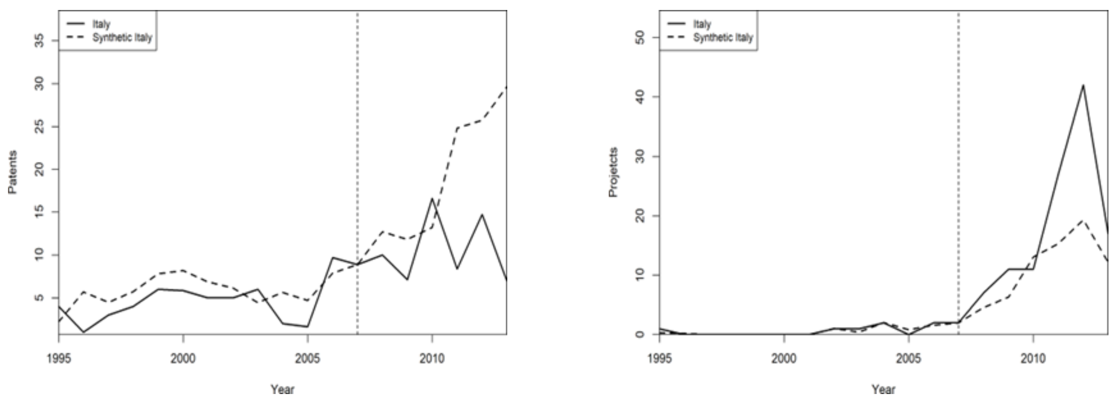
In contrast, in Italy, we observe an increase in the number of innovation projects followed by the regulatory innovation incentive in 2007 (Figure 5a). However, we find no significant effect on the number of patent applications (Figure 5b). Due to space reasons, we will focus on the significant models, namely the patent analysis in the UK and the case of number of innovation project in Italy[12]. It is, however, noteworthy that the absence of statistically significant results can be interpreted as the ineffectiveness of the cost pass-through incentive in the UK to increase the number of smart-grid projects and the WACC to incentivize patent applications in Italy.

[11] The ECI index is calculated based on the average complexity of the country's export with international comparative advantage, weighted by their share in the countries' overall exports (Hausmann, 2013).
[12] The post-/pre- MSPE test indicating the non-significance of models are in Appendix D, figures D.1 and D.2.



(a) Patent Application **(b) Smart-grid Projects**

Figure 4: Synthetic Control Model: UK



(a) Patent Application **(b) Smart-grid Projects**

Figure 5: Synthetic Control Model: Italy

Tables 1 and 2 present the covariates fit estimated the synthetic control for patent applications in the UK and smart-grid projects in Italy. The synthetic controls were estimated based on the combination of donor countries that were closer to the pre-innovation-stimuli-regulation of the two countries, given the covariates and output variables in each model.

Comparing the pretreatment characteristics of the actual UK with its synthetic control and the weighted average of the 13 reference countries composing the donor pool (Table 1). The synthetic control provides a more compatible control group for the UK since the means closely approximate the real UK in most covariates. The only variable that is not closely matched is the renewable share, given the difficulty of estimating a counterfactual signalized by the average in the other countries, which are distant from the real

UK. In the case of Italy, the covariate balance of the smart grid projects (Table 2) and the synthetic control demonstrate a close balance across all variables. The covariates are valuable estimators to support a satisfactory match for the synthetic control, since they mimic the treated unit better if the intervention had not happened (Abadie et al., 2010). However, there are limitations in finding good matches, especially when using a small number of units in the donor pool. Therefore, we perform sensitivity checks to verify the confidence and validity of the results.

Table 1: Synthetic Control Covariate Balance: Patents application in the UK (1995-2013)

	United Kingdom		All controls
Variables	**Real**	**Synthetic**	**Mean**
Electricity (log)	5.57	5.5	4.92
Renewables (share)	2.73	11.1	22.67
GDP (per capita)	31124.84	25653.21	21317.1
Complexity	1.98	1.51	1.18
Patent Application 2001	11	11.96	2.06
Patent Application 2005	7.12	6.86	2.48

Note: We set lags in 2001 and 2005 for the economic predictor's outcome.

Table 2: Synthetic Control Covariate Balance: Smart-grid projects in Italy (1995-2013)

	Italy		All controls
Variables	**Real**	**Synthetic**	**Mean**
Electricity (log)	5.46	5.16	4.95
Renewables (share)	17.39	17.33	22.44
GDP (per capita)	28164.24	27699.13	26273.25
Complexity	1.50	1.29	1.17
Patent Application 2002	1.00	1.01	1.31
Patent Application 2007	2.00	2.00	2.46

Note: We set lags in 2002 and 2007 for the economic predictor's outcome.

Table 3 demonstrates the synthetic control unit weights for both SCM under analysis. Despite using the same countries, the estimations vary given the differences in the outcome variables and covariates of the treated countries. In the synthetic UK case, the weights come mostly from Belgium and France, together accounting for 0.84, and Spain for 0.16. In synthetic Italy, the countries' weights are more diverse. Belgium and France account for 0.59, Turkey and Austria, a combined share of 0.32, and Ireland 0.09 of the synthetic control. The other donor countries were assigned zero W -weights in our estimation.

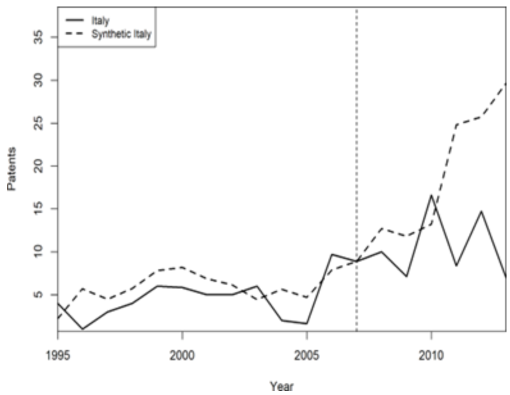
Table 3: Synthetic Control Unit Weight

Country	Patents: United Kingdom	Projects: Italy
Austria	0	0.12
Belgium	0.2	0.29
Finland	0	0
France	0.64	0.3
Greece	0	0
Hungary	0	0
Ireland	0	0.09
Netherlands	0	0
Norway	0	0
Poland	0	0
Slovakia	0	0
Spain	0.16	0
Turkey	0	0.2

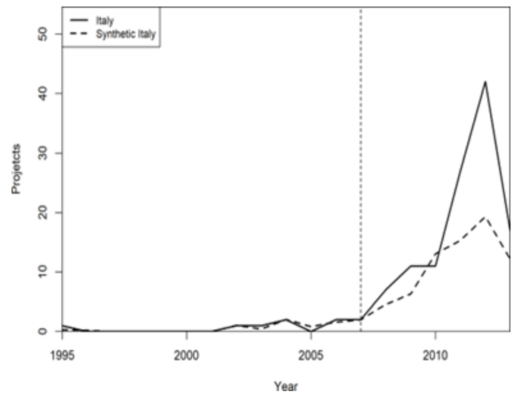
To assess the significance of our estimation, we performed a placebo test (Figure 6). The gray lines in Figure 6 present the treatment effects for countries that did not initiate an innovation incentive policy, and the synthetic control of each of these countries is normalized to the 0 lines. The results allow us to observe whether the treatment effect differs from statistical noise. If the placebo creates gaps similar to those estimated for our treated counties, our interpretation is that our analysis does not provide significant evidence of its effect. However, when the placebo presents a gap larger than others for our treated countries, we might infer that our estimation provides significant evidence of positive/negative innovation-stimuli regulation effect.

The figures 6a and 6b illustrate the result of this placebo analysis, with gray lines representing the "treatment effect" of the control countries and the dark black line representing the effect of the treated country. Our synthetic control estimations for the treated countries are consistently higher than the others. To ensure that the synthetic control for the placebo countries is estimated correctly, we follow Abadie et al. (2010) and exclude units with extreme values that are not comparable by controlling for the MSPE pre-intervention by discarding countries with a pre-intervention MSPE ≤ 2 times higher than the pre-intervention MSPE.

To estimate the effect of our synthetic control, the differences between the post-intervention outcomes in the treated unit and the synthetic control were calculated (Bonander et al., 2021). Our SCM for patent application in the UK had, on average, an increase of 9.14 patent applications per year after the intervention. Smart grid projects in Italy had an average increase of 6.31 smart grid projects per year after the regulatory intervention. Both results are in line with the literature on the topic that investigates the increase in investments after introducing the innovation-stimuli regulation of 7.4 patents on the treated countries (Ribeiro et al., 2023).



(a) Patents application gap in the UK and 13 control countries. Discard countries with pre-intervention MSPE ≤ 2 times higher than the pre-intervention MSPE for UK

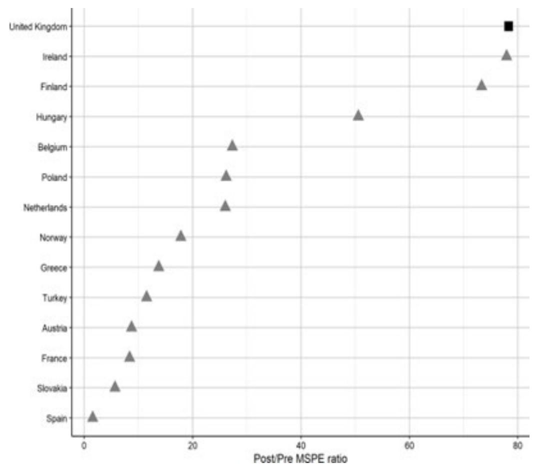


(b) Smart-grid projects gap in Italy and 13 control countries. Discard countries with pre-intervention MSPE ≤ 2 times higher than the pre-intervention MSPE for Italy

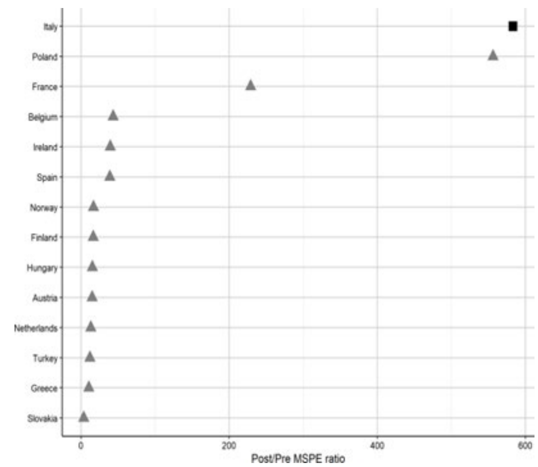
Figure 6: Placebo test

To test the validity of our SCM estimation, we estimated the MSPE for the UK and Italy and placebos in patent application and smart-grid projects, respectively, before and after interventions. This inference method divides the post-treatment MSPE by the pre-treatment MSPE of each unit and their synthetic control for each unit in the sample, which was first proposed in Abadie et al. (2010). The MSPE test indicates the distances between the unit and the synthetic control. The higher MSPE indicates a large discrepancy between the treated and control, allowing us to infer a higher treatment effect in the period under analysis.

Figures 7a and 7b provide the post-/pre-MSPE ratio of the countries with the size of the estimated effects standardized by pre-intervention fit in all states in the data and ordered from largest to smallest effect. In both tests, the patent application in the UK and the smart-grids project in Italy exhibit the largest discrepancy between treated and control after the event. This result can be expressed as a permutation-based p-value by dividing the rank of the treated unit (1, the highest) by the total number of units in the data (Abadie et al., 2010): 1/14, so the chances of obtaining a ratio as high as this one would be 1/14 or 0.071. This test strengthens the evidence of an actual effect being captured in our synthetic control models.



a) Patent application United Kingdom



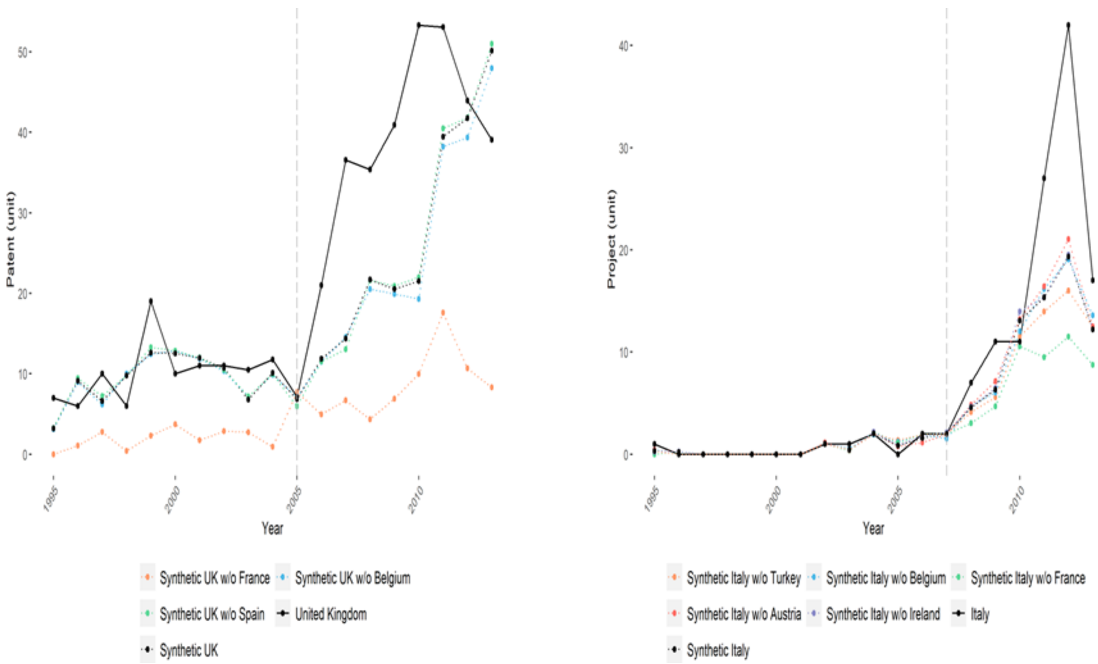
(b) Smart-grid projects Italy

Figure 7: pre/post-Innovation Stimuli regulation MSPE

5.2 Robustness Checks

To check the robustness of our results, we conducted the so-called falsification tests, which are the "in-time placebo" and the "leave-one-out procedure". The in-time placebo consists of comparing the situation in which the synthetic control happened in a period before and verifying if the model produces an estimated larger effect than the synthetic control results of the actual intervention period (Abadie et al., 2015). To perform this test, we estimated an earlier treatment year for the UK in 2000 and Italy in 2002. Changing the treatment year does not produce significant results because the effect only started after the treatment year, showing that our algorithm predicts the effect (Appendix E, Figures E.1 and E.2).

The leave-one-out procedure consists of individually interacting with the countries that received a positive weight in our Table 3. Figure 8a represents the synthetic control models of the UK without Belgium, France, and Spain (the colored dashed line indicates the synthetic UK without the mentioned control). In most cases, the pre-2005 fit without these countries is compatible with our main model, but the pre-2005 fit is worse without France. This is expected since France accounts for two-thirds of the UK's synthetic control. Hence, France's exclusion reduces the quality of the synthetic control. But the synthetic control is robust to leaving out other countries, and is below the increase in the UK. For Italy (figure 8b), when performing the same test without Austria, Belgium, France, Ireland, and Turkey (the colored dashed line indicates synthetic Italy without the mentioned control). The results of each new synthetic control are compatible with the previous estimations and are below the increase in smart-grid projects verified in Italy.



(a) Patent application United Kingdom

(b) Smart-grid projects Italy

Figure 8: Leave-one-out Test – The UK and Italy

After performing the synthetic control robustness checks and verifying the consistency of the gap between the UK and Italy and its synthetic controls in both estimations, we can assume that these results are not driven by pure chance and that there is an effect. However, one criticism of SCM is the strong assumption of mimicking the pre-treatment outcome of the treated country.

An alternative robustness check is the SDID method, which re-weights the control units to create a parallel pre-trend (Arkhangelsky et al., 2021). The re-weighting process is conducted on a subset of the pre-intervention periods, selected so that the weighted average of historical outcomes predicts average treatment period outcomes for control units. The pre-trend is not required to be identical to the treated unit pre-intervention period because SDID does not give any country a particularly high influence. With SDID after weighting, the estimator has no excessive variance using concentrated weights (see Appendix F). After this re-weighting, the SDID applies a DID analysis to estimate the effect on this re-weighted panel depicted in Appendix G.

In the SDID, through the placebo iterations estimation, the variance of the SDID estimator is calculated to conduct inference. Tables 4 and 5 present our average treatment effect of the treated (ATT) using the SDID method and its standard errors, and p-values were estimated through a placebo after 500 iterations for the UK and Italy, respectively. According to Arkhangelsky et al. (2021), the placebo method is only suitable for cases where only one unit is exposed to the treatment. The SDID results confirm the SCM results in patent applications in the UK and smart-grid projects in Italy. Regarding patents in the UK, there was a significant increase in the ATT effect of 21.12, and the smart-grid projects indicate a marginally significant (90% confidence interval) of 8.18 after the treatment. In Italy, the SDID estimations were closer to the SCM result, and the ATT is 10.51 for smart-grid projects, and the patent applications had a nonsignificant result.

The robustness check using SDID confirms the findings obtained by synthetic control estimation, but the effects are higher. Arkhangelsky et al. (2021) identified disparities in the estimations derived from SCM and SDID methods. Notably, the authors stress that SCM may underestimate the effects while including time weights and unit fixed effects in the SDID method leads to a more precise estimation. Despite this argument, we retained the more conservative results.

Table 4: Synthetic Difference-in-Differences: United Kingdom

Dependent Variable	ATT	Standard Error	t	P-value	CI Lower	CI Upper
Patent	21.12	7.58	2.79	0.02**	6.26	35.98
Projects	8.18	4.32	1.89	0.08*	-0.29	16.65

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Synthetic Difference-in-Differences: Italy

Dependent Variable	ATT	Standard Error	t	P-value	CI Lower	CI Upper
Patent	1.36	7.51	0.18	0.86	-13.36	16.08
Projects	10.16	4.09	2.48	0.03**	2.15	18.17

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

5.3 Descriptive Analysis

To better understand the composition of the treatment effects, we performed a descriptive analysis of the patent application and smart grid project data. Figure 9 depicts the number of patent applications in both countries between 1995-2013 and their categorization according to the stakeholders that applied for them. In both countries, we observed a stagnation in the number of patent applications just before introducing the innovation-stimuli regulation. In the post-intervention period, there was a steep increase in the number of patent applications, especially in the UK. The number of patent applications in Italy also increased, with slight anticipation of the regulatory intervention in 2006; however, its number remained stable throughout the following years.

Analyzing the organizations deploying the patent applications, we find a high share of patent applications coming from equipment suppliers, which are known for being the main stakeholders for innovation in the regulated sector (Pavitt, 1984; Miozzo and Soete, 2001). There is also an increasing share of patents in the electricity sector applied by "Services" firms, which comprehends especially the ICT companies responsible for producing technologies that control, manage, and monitor the smart grid's operation. Other organizations that applied for patents on a smaller scale were the research institutions and utilities. In research institutions, the increasing number of patent applications after the regulation intervention can be related to increasing participation in smart grid projects through the European Commission and LCNF funding lines, which allow cooperation with these actors. Despite suppliers and service companies not being the main recipients of innovation-stimuli regulation, the regulation in the UK seems to favor this spillover effect. In Italy, most patents were applied for by suppliers and service firms, and after the intervention, the average number of patent applications only marginally increased and was still comparatively lower.

The black dashed line in Figure 10 depicts the total number of smart grid projects conducted by both countries from 1995-2013, and the number of organizations participating in these projects is depicted on the stacked bars. The number of smart grid projects in both countries is comparable, and there was a spike in implemented smart grid projects in 2012 when Italy slightly surpassed the UK. Regarding the number of participants, it is slightly higher in Italy.

When examining the funding sources supporting these projects, it unveils higher participation of the European Commission funding smart grid projects in Italy were 27 (58.8%) and 16 in the UK 16 (37.2%)[13]. Despite the relevant participation of the European Commission in the UK, the influence of Ofgem is evident. Additionally, the UK has other public resources allocated to smart grid projects that fund 51.2% of the projects. In Italy, only after Decision n. 39/2010, projects started to be supported by the Arera. However, this fund was not sustained in the following years, and other financial resources for the smart grid were scarce. In Italy, Arera and national funds supported 6 (17.6%) of the smart-grid projects, indicating that the increase in Italy's smart-grid projects was due to European Commission funding and less to the WACC regulation.

[13] Appendix H exhibits the share of all types of funding sources for smart-grids projects in the UK and Italy, respectively, in Figure H.1 and H.2.

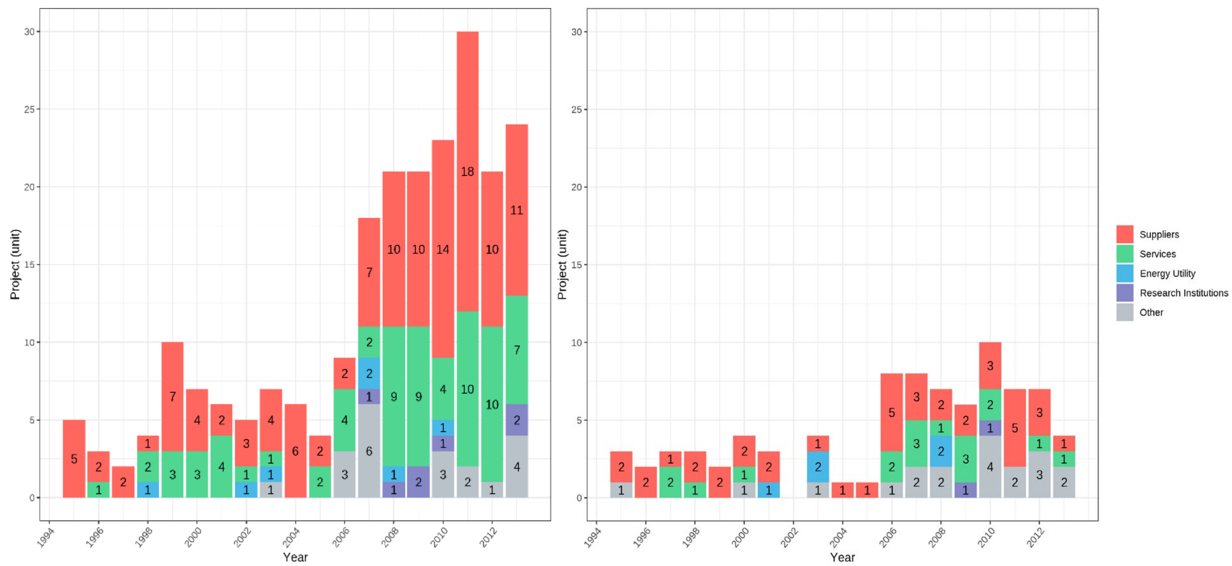


Figure 9: Evolution of Patent Applications (1995-2013) (Source: Authors)

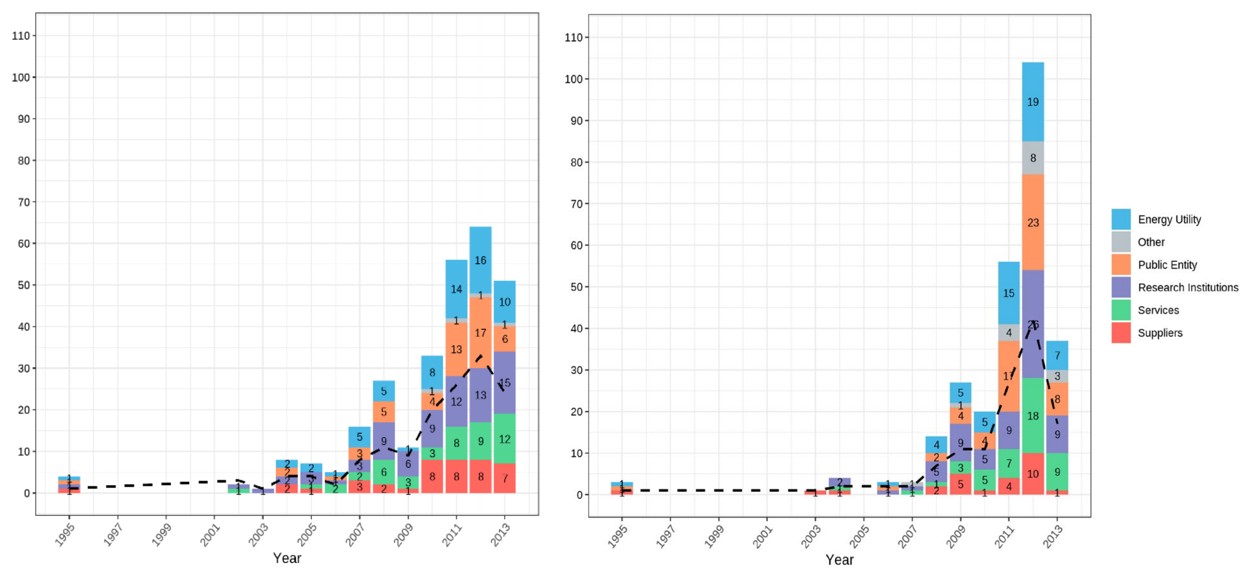


Figure 10: Evolution of Smart-grids projects and Organizations (1995-2013) (Source: Authors)

Note: "Research Institutions" refers to Universities and Research Centers. "Energy Utility" includes generators, distributors, transmitters, and retail firms. "Suppliers" constitute firms that produce machinery and equipment used by Energy Companies. "Services" compiles the "information and communications technology (ICT)" that works on wireless telecommunication to internet technologies applied to cars, buildings, and housing equipment, as well as consultancies. "Public Entity" is an organization controlled by the government. Lastly, "Other" refers to firms not classified in the formerly mentioned categories. In Figure 10 the dashed black line consists of the sum of smart-grid projects in the year.

When analyzing the overlap in the UK and Italy countries on organizations participating in the smart grid projects and applying for patents, a quasi-inverse relationship is revealed. Organizations participating in more smart grid projects are not the same as the ones with more patent applications (Figures 11 and 12). Organizations with more patent applications in both countries are equipment suppliers and ICT firms. Conversely, the organizations participating in more smart grid projects are utilities and research institutions. Regarding patent applications, there are additional differences in the patterns of the UK and Italy. While organizations in the UK applied for more than one patent, this number was restricted to one patent application per organization in Italy.

Another difference is related to the organizations participating in the smart-grid projects. In projects supported by Ofgem, utilities account for 36.9%, suppliers and services 25%, public entities 21.9%, research institutions 15.6%, and others 0.6%. In projects supported by Arera, 47.6% of the participants were public entities, utilities account for 42.9%, and both suppliers and services 9.6% (Appendix I show the share of the organizations participating in smart-grids projects financed by the NRAs). The higher share of suppliers and ICT firms (services) categories in the UK reflects higher support for cooperation promoted by Ofgem. In contrast, Arera regulation focused on utilities and the application of these technologies in sites owned by public entities, with little incentive for cooperation with other organizations.

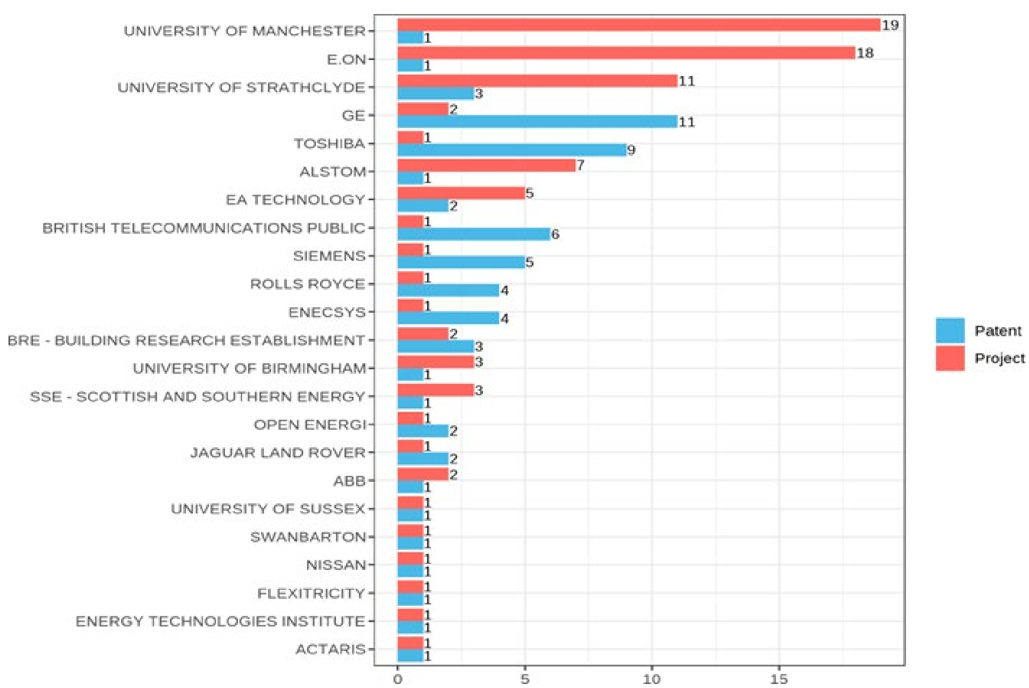


Figure 11: Smart-grids projects and patent application overlap: United Kingdom (Source: Authors)

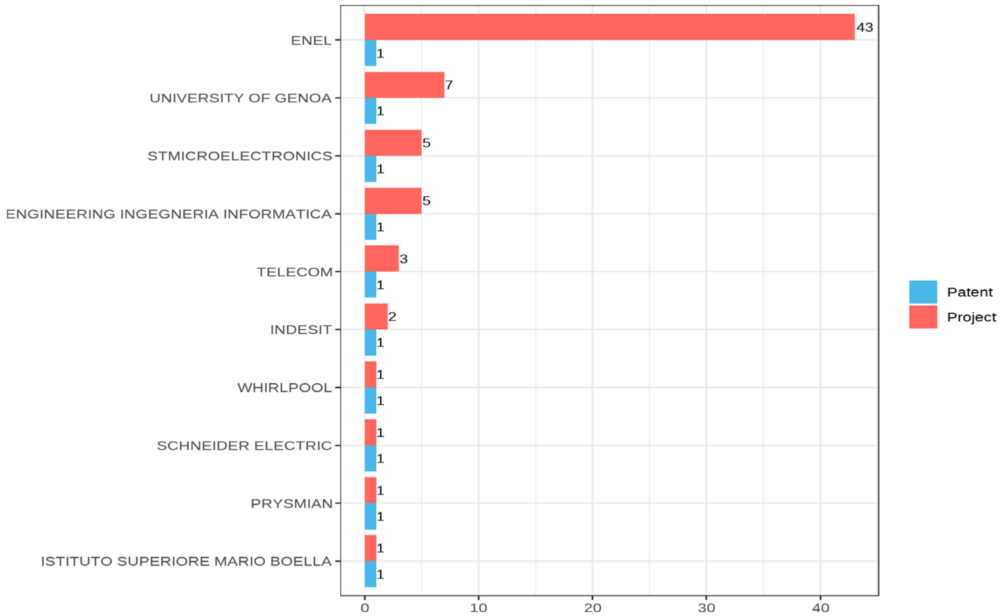


Figure 12: Smart-grids projects and patent application overlap: Italy (Source: Authors)

6. Discussion

The results indicate that the UK cost-pass through approach had a more consistent and positive effect on innovation outcomes than other innovation-stimuli regulations, particularly in terms of patent applications. This affirmation is supported by the significant increase in UK patent applications despite the number of smart grid projects remaining similar to the synthetic UK estimates. This effect seems to be related to the generous, consistent and long-term regulatory approach by Ofgem, which since the introduction of the IFI, increased the share of R&D spending based on utility revenue from 0.5% to 2.3% (Lockwood, 2016; Jamasb and Pollitt, 2015).

The cost-pass through model was common in pre-deregulation years to finance R&D investments by the utilities (Sanyal and Ghosh, 2013). Therefore, when designing this provision, Ofgem provided an analogous mechanism that positively impacted innovation outputs. The better performance of cost pass-through in patent applications might be related to reducing financial risks, by lowering the cost of capital for R&D projects. Furthermore, Ofgem incentivizes collaboration with other stakeholders in innovation projects. These cooperations among stakeholders with a higher capacity to be innovative, such as suppliers and services companies, appear to have facilitated more patent applications (Miozzo and Soete, 2001) and might have supported a "crowing in" effect from the private energy sector (Nemet and Kammen, 2007).

Conversely, Italy adopted a regulatory approach restrict to projects that demonstrated financial viability employing an emerging technology, with high financial and technological risks in spite of the risk premium. As a consequence, the WACC incentive was limited to a few projects, and most of Italy's R&D smart-grids projects were supported by EU funding. With respect to the limited number of patent applications, this result might be related to the restricted involvement of equipment suppliers and ICT firms in these projects, and an existing innovation ecosystem less prone to innovation in this technology[14]. Therefore, the limitation of the incentives, low cooperation with equipment suppliers and ICT firms, and previous lack of expertise in smart grid technologies might have led to no significant impact on the trend of patent applications after the intervention.

Despite the UK's regulatory schemes having considerably supported reversing the decline of patent applications after liberalization, it might not show the real cost of innovation in the sector, especially for the customers. For instance, the total amount invested in WACC in Italy was estimated at 16.5 million euros, which is roughly equivalent to the investment made by UK utilities in IFI, which was £13.8 million[15], without including the Ofgem contribution. It is noteworthy that in the UK, customers paid a significant portion of these investments. For instance, LCNF had a cost of £500 million.

7. Conclusions

Our study provides a detailed analysis of the effects of innovation-stimuli regulation applied in the UK and Italy. The findings are directly relevant for regulatory authorities and utilities and for the design of innovation-stimuli incentives and frameworks.

The positive effects from cost-pass through seem to be related to a high degree of flexibility, long-term consistency and amount of the regulator in supporting R&D investments. Furthermore, the cooperation between utilities, suppliers and services (ICT and telecommunications firms) have supported the higher patent application level. Considering the LCNF has a policy design similar to the RIIO on their mechanism to foster innovation, we could expect that RIIO to have comparable effects on innovation output. On the other hand, the WACC approach has shown limited effect on incentivizing innovation outputs, such as R&D projects and patent applications. The WACC-based incentive mechanism does not seem to have been

[14] Indicators on entrepreneurship which are highly related to innovation, highlight the UK leadership as the 4th most open country to entrepreneurs, while Italy was in the 42nd position, according to the Global Entrepreneurship Index (2018) from the GEDI (The Global Entrepreneurship and Development Institute).

[15] When £13.8 million is converted to euros using the average exchange rate in 2010 of 1.166 euros to a pound, the amount in euros corresponds to 16.1 million. Without considering the 2% premium of £3.7 million, or 4,3 million euros, in WACC Premium.

effective in reversing the downward trend and increase R&D increase after the liberalization.

Another contribution from our study is the application of new methods, the SCM and SDID, to analyze the impact of incentives on the innovation outputs in regulated electricity distribution network utilities. The advantage of using SCM and SDID is the possibility of using robust causal inferences when it is difficult to find adequate counterfactuals, which is a key challenge in innovation incentive regulation studies.

For future research, it would be useful to evaluate the effect of other innovation-stimuli regulations introduced in recent years, such as the RIIO in the UK. Another important area is to study the extent to which the consumers benefit from the innovation-stimuli regulations, given the considerable amount of investment and effort in this area.

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Appendix A. Literature Review - Summary

Major Topic	Reference	Research Question	Sample Period	Method	Dependent Variable	Key Results
Impact of Liberalization on Electricity	Nemet Kammen (2007)	Causes of R&D decline in the US after deregulation crowd out private sector investments	US (1970-2005)	Descriptive Statistics Regression	Applied Patents, patent citations R&D expenditure (Public and Private)	Private and Public R&D spending decline and government R&D initiatives are associated with higher R&D investments by private investors
	Jamasb Pollitt (2008)	Causes of R&D spending decline after liberalization	Scientific Papers (1974-2004)	Literature Review Descriptive Statistics	R&D expenditure	Short-term R&D productivity and innovation increase. However, decline in R&D spending and negative long-term effect on innovation
	Jamasb Pollitt (2011)	Effect of liberalization on patenting activity	UK (1958-2008)	Descriptive Statistics	Filed patents by firms	Electricity-related patents increased after liberalization but long-term decline in R&D spending
	Sterlacchini (2012)	Effect of liberalization and privatization on R&D expenditure of electric utilities	US, Europe and Japan (2000-2007)	OLS regressions	R&D expenditures/sales and EBITDA/sales	R&D expenditure decrease was stronger in private private electric utilities
	Sanyal Gosh (2013)	Innovation response of upstream technology suppliers after the liberalization of electricity sector	2,000 US firms (1976-2006)	Difference-in-difference	Applied Patents citations	Decline in quantity and quality of patenting after liberalization
	Jamasb Pollitt (2015)	Impact of electricity market reforms on	UK (1958-2012)	Descriptive Statistics	Applied Patents and R&D expenditure of electricity firms	R&D expenditure and innovation output is increasing due to

		innovation in the UK on R&D spending and patenting activities				regulatory framework supporting R&D (IFI and LCNF)
	Cambini et al. (2016)	Impact of market regulation level on innovation activities	16 European countries (1990-2009)	Poisson regression with fixed-effects	Filed patents	Increasing in patenting activities after deregulation with policies aiming to reduce vertical integration
	Marino et al. (2019)	Effect of deregulation on innovation in the electricity sector	31 OECD countries (1985-2010)	Difference-in-difference	Granted Patent	Positive effect in countries with weak liberalization and negative in countries with a drastic liberalization
	Marques et al. (2014)	Impact of cost-plus and price cap regulation on stimulating smart grid investments	Portugal (2012)	Model	Price Level	Cost-plus and price-cap regulatory approach remains uncertain to incentive smart grids. New and improved regulatory instruments might be required
Impact of Regulation on Innovation in Electricity	Abrardi et al. (2018)	Impact of the regulatory environment on utilities' investments	18 energy and gas utilities in 4 European countries (1997-2013)	Regression with fixed-effects	Investment rate	Incentive regulation increases investments and encourage innovation rate of utilities compared to rate of return. WACC has a positive impact on investments
	Poudineh et al. (2020)	Ways to incentivize innovation in network industries	Firms	Model simulations	Efficiency and innovation gain and competition for innovation funds	Regulatory models based on cost- efficiency may not effectively promote innovation. Innovation requires different incentive approach
	Marques et al (2022)	Suitability of regulatory model to incentive investments in new technologies	Analysis applied to technologies: advanced metering infrastructure, advanced substation and feeder automation,	Decision Model	Amount invested in innovative technology	Regulatory schemes should adapt to the specificities of each type of innovation investment

			and microgrids			
Innovation-Stimuli Regulation on Electricity	Cambini et al. (2016)	Impact of market and regulation on smart grids investments	30 European countries (2002-2014)	Descriptive Statistics Statistical Analyses	Smart-grid investment	Lower market concentration, incentive-based regulation and adoption of innovation-stimulus mechanism enable smart grids investments
	Cambini et al. (2020)	Different approaches to fostered innovation in the energy sector	6 European countries	Case-study	Regulatory Framework	Large difference among regulators in the approaches to support. Government-driven approach show higher levels of investment in innovation
	Jamasb et al. (2021)	Regulatory mechanisms available to incentive innovation in the energy network	European countries	Case-study	Regulatory Framework	A "value-based" approach, more than "cost-efficiency" is advisable to incentive innovation. Innovation stimulus spending should be considered an investment
	Anaya et al. (2022)	How to achieve optimal regulation of the electricity distribution system operator (DSO)	20 European countries 39 DSOs and 12 NRAs (2020)	Survey	Regulatory Framework	NRAs can play an important role in promoting innovative DSO activities by establishing explicit funding
	Ribeiro et al. (2023)	Impact of innovation-stimuli regulation on innovation outcomes	21 European countries	Difference-in-difference	Patent application	Positive impact of innovation-stimuli regulation on patenting, and stronger effect in the early adopters

Appendix B. Patent Codes: Smart Grids

Table B.1: Smart-grids CPC Classes

TOPIC	CPC CLASSES	DESCRIPTION
Systems integration and efficiency	Y02E 40/70	Smart grids as climate change mitigation technology in the energy generation sector
	Y04S 10/00 (subclasses: 10/12, 10/123, 10/126, 10/14, 10/16,10/18, 10/20, 10/22, 10/30,10/40, 10/50, 10/52)	Systems supporting electrical power generation, transmission, or distribution
Smart grids in buildings	Y02B 70/30 (subclasses: 70/3225, 70/34)	Systems integrating technologies related to power network operation and communication or information technologies
	Y02B 90/20	Smart grids as enabling technology in buildings sector
ICTs applications to smart grids	Y04S 40/00 (subclasses: 40/12, 40/121, 40/124, 40/126, 40/128,20/18, 40/20)	Systems for electrical power generation, transmis sion, distribution or end-user application management characterized by using communication or information technologies, or communication or information technology specific aspects supporting them
	Y04S 50/00 (subclasses: 50/10,50/12, 50/14, 60/16)	Systems supporting electrical power generation, transmission or distribution
End-user applications	Y04S 20/00 (subclasses: 20/12, 20/14, 20/20, 20/221, 20/222,20/242, 20/244, 20/246, 20/248,20/30)	Systems supporting the management or operation of end-user stationary applications, including the last stages of power distribution and the control, monitoring or operating management systems at local level

Source: Smart-grid patents' classes retrieved from Gregoire-Zawilski and Popp, (2022).

Appendix C. Selection of Predictor Variables

Table C.1: Fixed-Effect Regression for selection of predictor variables.

	Patent Application	Smart-grid Projects
GDP (per Capita)	−0.0002***	−0.0001*
	(0.0001)	(0.00004)
Electricity (log)	−13.200	−0.666
	(8.210)	(5.560)
Renewables (%)	−0.260***	0.078
	(0.097)	(0.066)
Complexity	−17.100***	−11.100***
	(2.450)	(1.660)
Unit fixed-effects	Yes	Yes
Time fixed-effects	Yes	Yes
Observations	315	315
R^2	0.163	0.177
Adjusted R^2	0.048	0.063
F Statistic (df = 4; 276)	13.500***	14.800***

Note: Driscoll-Kraay Standard Errors in Parentheses: *p<0.1; **p<0.05; ***p<0.01

Appendix D. Mean Squared Prediction Error (MSPE)

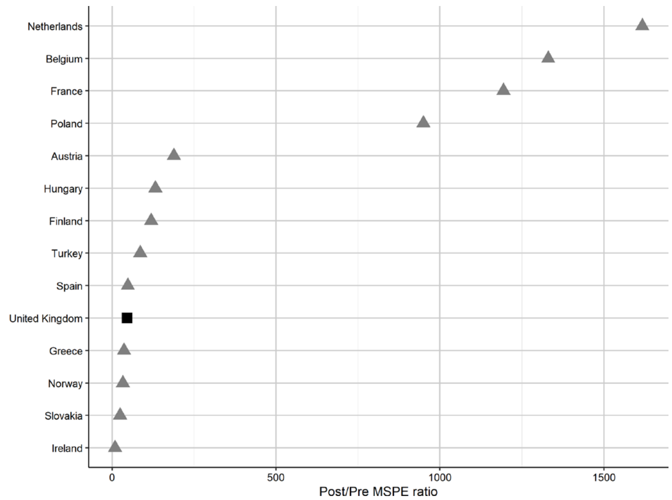


Figure D.1: pre/post-Innovation Stimuli regulation mean squared prediction error (MSPE): Smart-grid projects in the UK

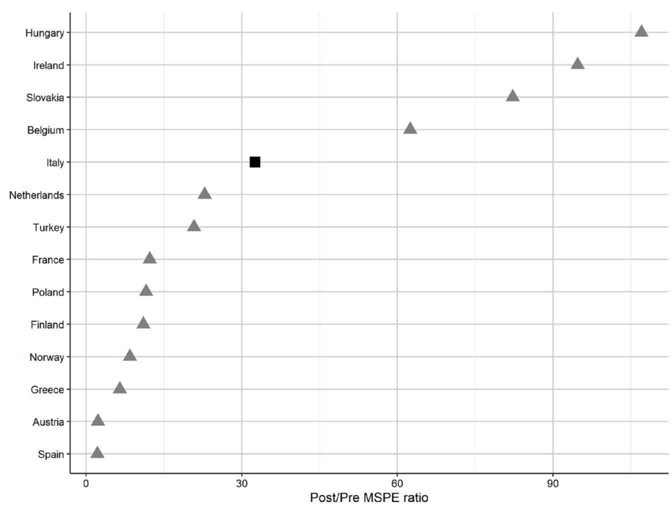


Figure D.2: pre/post-Innovation Stimuli regulation mean squared prediction error (MSPE): Patent application in Italy

Appendix E. In-Time Placebo Tests

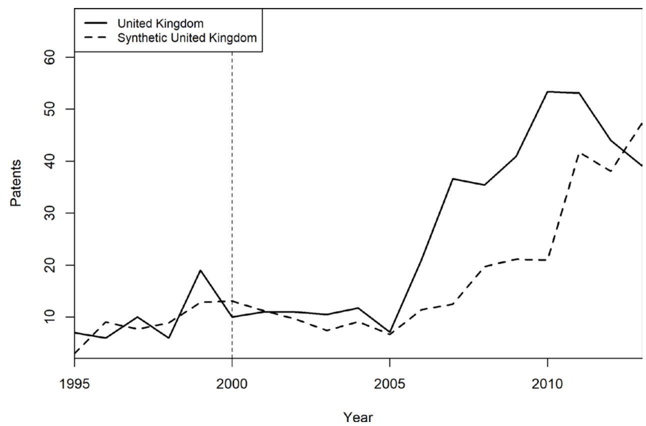


Figure E.1: In-Time Placebo Test: Patent Application UK (intervention: 2000)

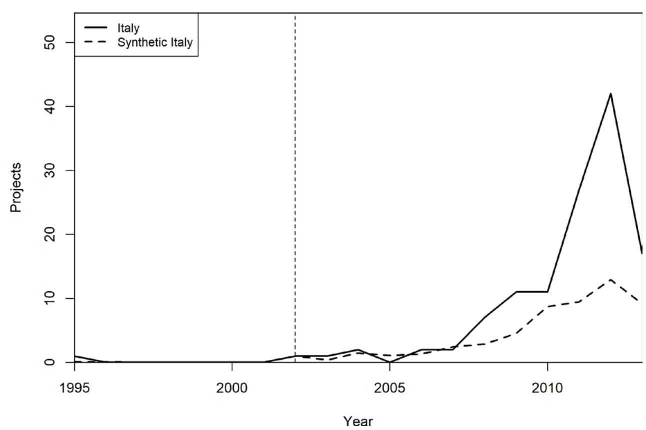
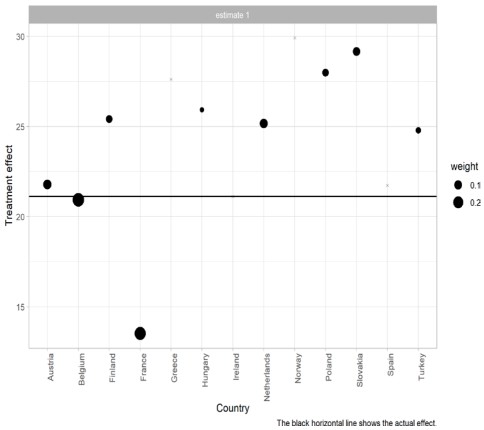
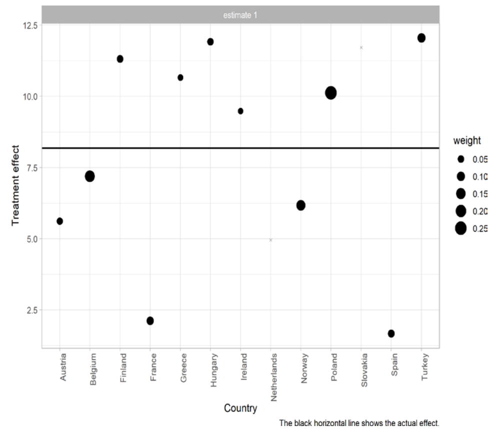


Figure E.2: In-Time Placebo Test: Smart-grid projects Italy (intervention: 2002)

Appendix F. Synthetic Difference-in-Differences: Controls

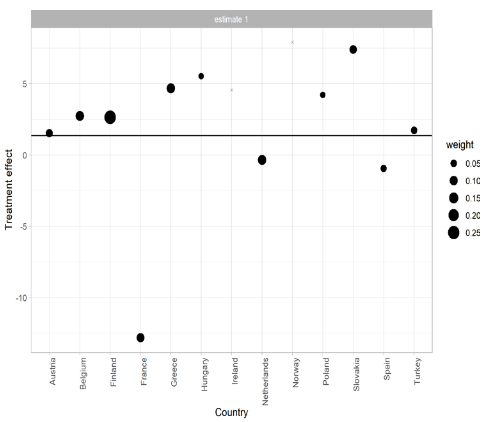


(a) Patent Application

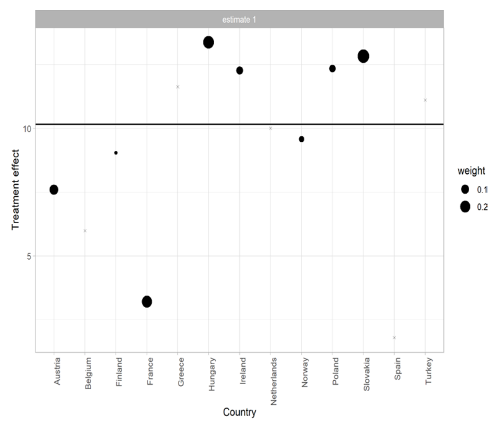


(b) Smart-grid Projects

Figure F.1: Synthetic Difference-in-Differences: UK



(a) Patent Application

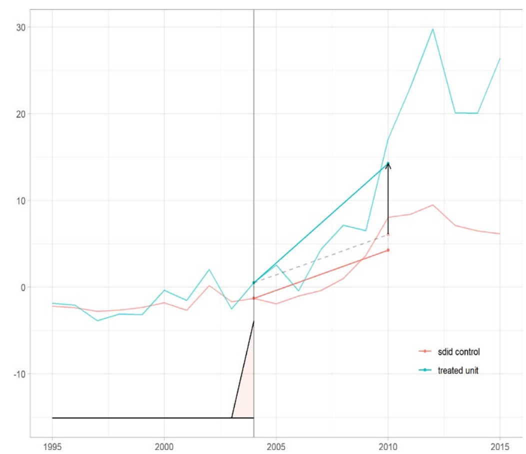


(b) Smart-grid Projects

Figure F.2: Synthetic Difference-in-Differences: Italy

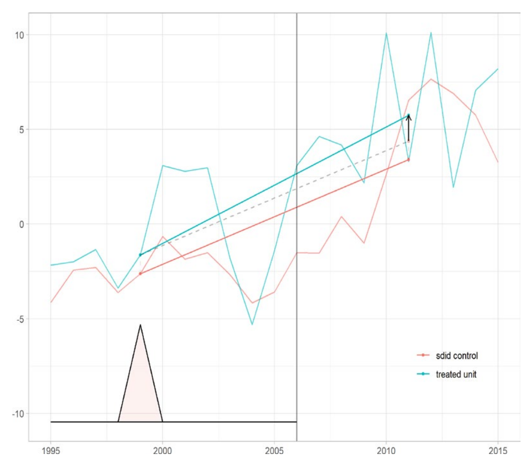
Appendix G. Synthetic Difference-in-Differences: Estimations

(a) Patent Application

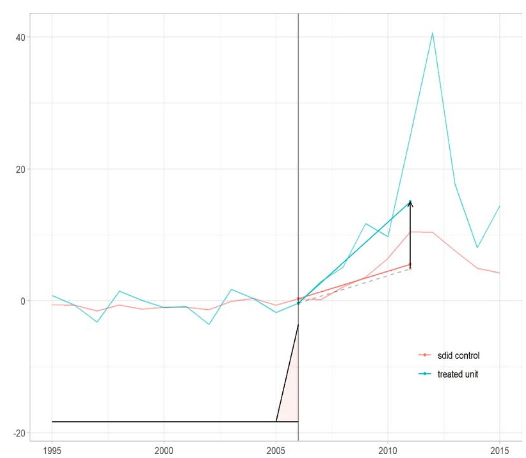


(b) Smart-grid Projects

Figure G.1: Synthetic Difference-in-Differences: UK



(a) Patent Application



(b) Smart-grid Projects

Figure G.2: Synthetic Difference-in-Differences: Italy

Appendix H. Smart-Grids Projects - Funding Bodies

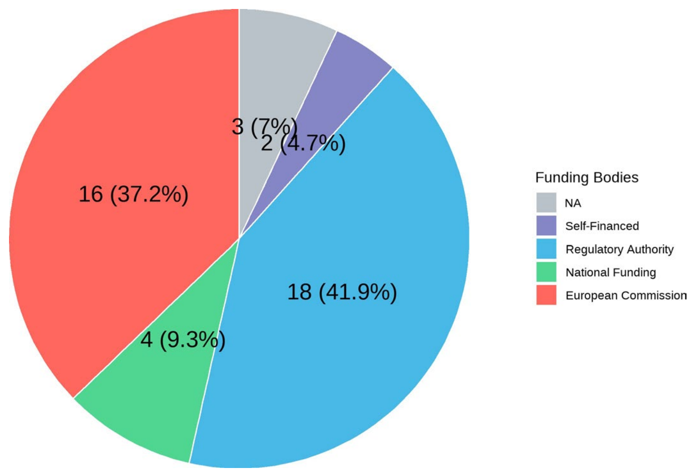


Figure H.1: Smart-grid projects Funding Bodies in the UK (Source: Authors)

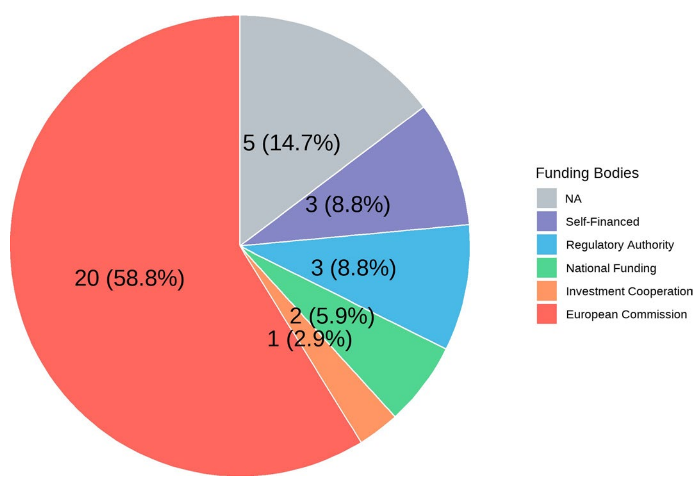


Figure H.2: Smart-grid projects Funding Bodies in Italy (Source: Authors)

Appendix I. NRA Smart-Grids Projects - Stakeholders

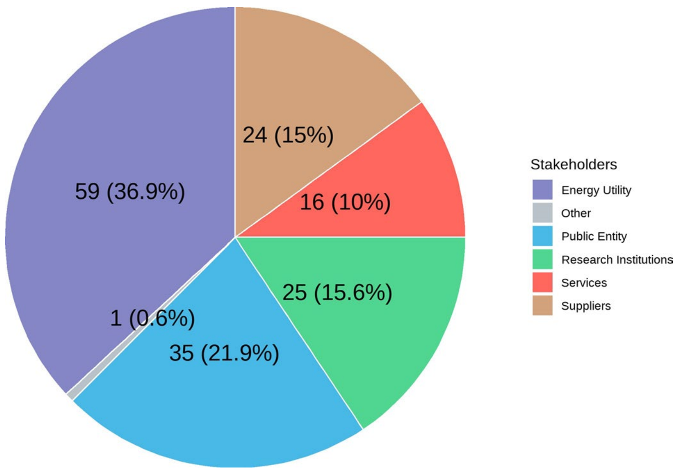


Figure I.1: Stakeholders participating in Smart-grid projects Funded by OFGEM in the UK (Source: Authors)

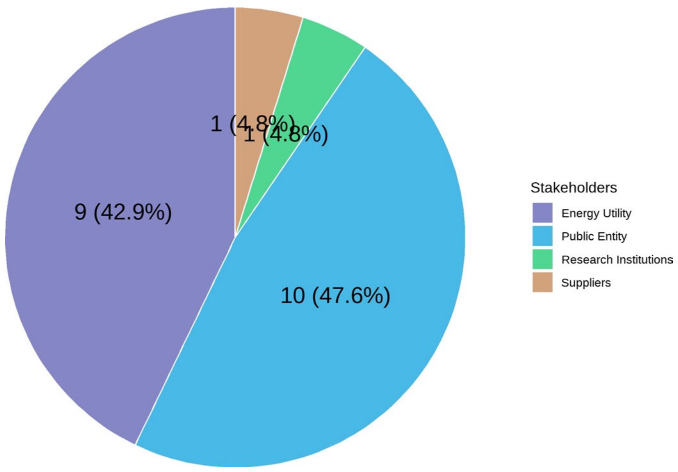


Figure I.2: Stakeholders participating in Smart-grid projects Funded by ARERA in Italy (Source: Authors)