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Cohesion Policy Incentives for *Collaborative Industrial Research*. The Evaluation of a Smart Specialisation Forerunner Programme[*]

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Abstract
This paper evaluates a program of subsidies for Collaborative Industrial Research (co-)funded by the EU Cohesion Policy in Italy mobilizing over 1 billion euros. This program anticipated in the 2007-2013 funding cycle some of the key features of Smart Specialization Strategy (S3) programmes, offering evidence-based insights on potential challenges to the practical application of the S3 approach. The programme was not successful in boosting investments, value added or employment of beneficiary firms. The collaborative dimension of the projects added limited value and a more generous level funding would have not improved effectiveness. However, positive impacts emerged in low tech sectors.

Keywords: Cohesion Policy, Smart Specialisation, Policy Evaluation, Innovation, European Union,
JEL Classifications: **O18, R11, R58**

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1. Introduction

The Smart Specialisation Strategy (usually referred to as S3) is a novel approach to the design and implementation of innovation policies. The Smart Specialisation concept emerged from the Knowledge for Growth expert group in the framework of the European Research Area (ERA) (Foray et al., 2009) as a means to explain the productivity gap between the US and Europe in terms of the differential penetration of Information and Communication Technologies in the two Continents. According to Foray et al. (2011), Smart specialisation is "… largely about the policy process to select and prioritise fields or areas where a cluster of activities should be developed, and to let entrepreneurs discover the right domains of future specialisation" (p. 7). The S3 approach advocates the concentration of public resources in a set of clearly defined pre-determined priority areas to be selected with a bottom-up approach based on a process of 'entrepreneurial discovery[1]' involving all relevant local stakeholders that together should cooperatively elaborate the best possible innovation strategy for their own developmental future. In this framework, each individual locality is supposed to embark in "a rigorous self-assessment of [its] knowledge assets, capabilities and competences and the key players between whom knowledge is transferred" (McCann, Ortega-Argiles, 2015, p. 3).

Despite being a recent concept with limited theoretical elaboration, supporting evidence and applications, the new approach recorded an unprecedented success on the European political market. Presented by the Foray group in 2009, it became a cornerstone of EU policies already in 2013 when the final deal on the 2014-2020 programming period was approved. Smart Specialisation is now a key component of the EU 2020 Innovation Plan as well as of the reformed EU Cohesion Policy, shaping both innovation and regional development policies of the EU. As a result the Smart Specialisation approach to innovation policies is currently being deployed in all countries and regions of the European Union (EU) representing an unprecedented shift from pre-existing innovation policies.

The evolution of EU innovation and Cohesion policies towards a Smart Specialisation approach was so rapid that it allowed very limited room for small-scale trialing of programme inspired by the proposed paradigm or for policy learning before large scale implementation. The new practices and procedures established in the 2014-2020 programming period lack a wide evidence basis on their effectiveness and value added (for example in comparison with pre-existing policies) and suffer from a limited understanding of what works (and what does not) in practice in different contexts. This paper aims to fill this gap by exploiting as 'experimental field' the unique features of a large innovation programme implemented in Italy with the support of the 2007-2013 EU Cohesion Policy. This makes it possible to learn helpful lessons on the practical functioning and effectiveness of some the features that many regional innovation programmes have introduced in response to S3

[1] This process involves the search activities by entrepreneurs that identify the potential advantages of general purpose technologies in their own economic domain, as "entrepreneurs …. are in the best position to discover the domains of R&D and innovation in which a region is likely to excel given its existing capabilities and productive assets" (Foray et al.,2011, p. 7).

principles in the 2014-2020 programming period. It is far too early for any rigorous evaluation of actual 2014-2020 Smart Specialisation Programmes. Therefore the only feasible way to inform an evidence-based debate on how to maximize the returns to EU innovation policies as well as on the post-2020 strategies is to carefully scrutinize 'S3 forerunner programmes' from the past and try and learn from them.

We evaluate the ex-post impact of a program supporting industrial research in Italian less developed regions (the 'Mezzogiorno'). The Program - Collaborative Industrial Research (CIR) Programme - was co-financed by the European Union Cohesion Policy during the programming cycle 2007-13 and its design anticipated many of the practical features of 2014-2020 S3 programmes. In particular: a) funding (approximately 1 billion euros) was distributed to beneficiaries according to local demand for innovation activities (an embryonic local 'entrepreneurial discovery' process); b) the programme funded only specific pre-selected highly innovative ('smart') sectors; c) it aimed at stimulating collaboration between firms and among firms and Universities; d) it met transparency criteria for both the selection of projects to be financed (judged by independent committees) and their monitoring during implementation. Thanks to the scoring system that assigned CIR funding to individual applicant firms, it is possible to assess the impact of the program by means of state-of-the-art counterfactual methods. In particular, we compare firm performance within a bandwidth of the scoring threshold using Regression Discontinuity Design (RDD) techniques. We can evaluate the impact of the programme in terms of first-order effects on investments and second-order effects in terms of value added and employment. We also analyze the extent to which the specific 'S3-style' features of this program influence effectiveness. Finally, we provide far-from-the-threshold inference, by using the Angrist and Rokkanen (2015) conditional independence assumption (CIA). We are therefore able to predict what would have happened if firms with scores below the funding threshold (and therefore not funded) would have gained access to the scheme by virtue of a more generous funding of the programme. We can also predict whether – instead – public funds captured by firms whose scores were marginally above the funding threshold paid off or not, shedding light on the link between the scale of funding and impacts.

The empirical results offer a mixed picture. CIR did not produce any impact on the performance of the beneficiary firms in terms of investments, value added and employment. The results suggest that a more (or less) generous level funding of the programme would have not improved its effectiveness. The findings offer limited support for the practical benefits from the collaborative dimension of the projects or for the inclusion of research centres in the project partnerships. Conversely, the programme was more successful in supporting firms in low tech sectors, suggesting that these might be viable targets for well-balanced S3 programmes. Finally, the effectiveness of the scheme on value added (investment) is higher (lower) for firms with high patenting capacity, while there seems to be scant support for the idea that multinational corporations are key to successful innovative collaborations. These findings provide helpful insights on how to maximize the impacts of programmes inspired by the S3 strategy.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature in order to highlight the key gaps. Section 3 discusses the characteristic of the CIR programme and its points of contact with programmes currently being implemented under the S3 approach. Section 4 illustrates the data. Section 5 describes the identification strategy. The results are illustrated in Section 6 and Section 7 concludes with some reflections for post-2020 innovation and Cohesion policies.

2. The implementation of the Smart Specialisation Strategy: key knowledge gaps

The 'Lisbon Agenda' (European Commission 2000) aimed at making the EU "the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion" (Presidency Conclusions, par. 5). The Lisbon Agenda presented the generation of new (technological) knowledge as key to productivity and economic growth by fostering R&D investments that were expected to reach 3% of EU GDP by 2010. However, both the 2003 Sapir Report and the 2005 Mid-term review of the Lisbon Strategy highlighted the fundamental failure to achieve the proposed targets by means of a strategy exclusively focused on R&D. The 'Knowledge for growth expert group' (advising the European Commissioner for Research) seemed to provide a new solution to an 'old' EU problem: 'smart specialisation' as a means to 'address the grand challenge' (Foray et al. 2009).

"The question is whether there is a better alternative to a policy that spreads [R&D investment] thinly cross several frontier technology research fields, some in biotechnology, some in information technology, some in the several branches of nanotechnology, and, as a consequence, not making much of an impact in any one area. A more promising strategy appears to be to encourage investment in programs that will complement the country's other productive assets to create future domestic capability and interregional comparative advantage. We have termed this strategy 'smart specialisation'." (Foray et al. 2009, p.20)

'Smart specialisation' strategies posit that entrepreneurs should be supported in their search for the most promising technological sector to better target their investments. The 'Smart specialisation' is one of the key pillars of the EU2020 Strategy and its objectives to promote "smart, sustainable and inclusive economy delivering high levels of employment, productivity and social cohesion" (European Commission 2010, p.5). In particular the 'smart specialisation' pillar includes three 'flagship' initiatives largely reflecting the priorities of the 'smart specialisation strategy': 'Innovation Europe' (focused on R&D), 'Youth on the move' (focusing on Human Capital) and 'A digital Agenda for Europe' (targeting ICT). All EU policies should be designed in order to contribute to the achievement of the EU2020 strategy targets.

EU Cohesion Policy has fully internalised the Smart Specialisation approach (European Commission, 2010) by aiming to identify the optimal regional-level matching between innovation efforts, human capital and local industrial and technological advantages (McCann and Ortega-Argilés, 2015). "The geography of innovation is (…) very diverse with certain regions competing worldwide on the technological frontier, and other struggling to move closer to that frontier (…)"(European Commission, 2010 p. 3). However, the architecture of the 'new' 2014-2020 EU Cohesion Policy rests on the assumption that the 'smart specialisation' principles are applicable to all regions: "Innovation is important for all regions; for advanced ones to remain ahead and lagging ones to catch up" (European Commission, 2010 p.3). The process of 'entrepreneurial discovery' triggered by the Strategy is supposed to generate structural change through the inclusive process of stakeholder involvement and to make new activities (rather than sectors or individual firms) the core priorities (Foray, 2015; Morgan, 2016). Therefore, S3 requires stakeholders to have a global perspective on their potential competitive advantage, to be aware of their potential for cooperation, and to focus their efforts and resources on a limited number of ambitious realistic priorities through which creating a critical mass of research and development activities, leading to structural change and growth (Radosevic et al., 2017). S3 is therefore expected to allow EU countries and regions to 'strengthen their research and innovation systems, maximise knowledge flows, improve absorption and utilisation capacities as well as spread the benefits of innovation throughout their economies' (Hegyi and Rakhmatullin, 2017, p. 5).

Coherently with this approach the European Commission presents all EU regions with a portfolio of tools inspired by the smart specialisation approach to be selected, combined and coordinated in line with local needs: innovation clusters, innovation-friendly environment for Small and Medium-sized Enterprises (SMEs), life-long learning in research and innovation, regional research infrastructure and centres of competence, creativity and cultural industries, fast internet applications and easy access to on line contents, and the use of public procurement to support demand for innovative products and services.

What is the evidence on the impact of the innovation policy tools implemented so far by the EU regions? A recent comprehensive review[2] of impact evaluation analyses of publicly funded programmes supporting innovation highlighted that only 17 out of 42 papers reviewed identified some positive impact of active innovation policies on productivity (Aguiar and Gagnepain 2013; Grilli and Murtinu, 2012; Sissoko, 2013), employment (Benavente et al 2007; Moretti and Wilson, 2013; Morris and Herrmann, 2013; Einiö, 2014), or other measures of firm performance e.g., sales, turnover, profit (Nishimura and Okamuro, 2011; Jaffe and Le, 2015). Moreover, the review concluded that programs emphasizing public-private collaboration tend to perform better than those that exclusively support private firms and that only competitive subsidies have positive effects. Finally, the more general consolidated evidence is that evaluating the impact of R&D loans, subsidies and grants is extremely complex, even when individual programmes are relatively simple in terms of policy design and implementation. Only a limited number of impact evaluation studies

[2] We refer here to the report "Evidence Review 9 Innovation: grants, loans and subsidies" published in October 2015 by the What Works Centre for Local Economic Growth www.whatworksgrowth.org. The Centre is a collaboration between the London School of Economics and Political Science (LSE), Centre for Cities and Arup.

can directly trace the full range of policy effects; none of them can attribute these effects to specific features of the corresponding programme. If the existing literature is far from unanimous on the impact of active innovation policies on a variety of measures of firm performance, solid evidence on the returns to the novel features introduce by the Smart Specialisation Strategy is non-existent. Large part of the existing empirical literature on Smart Specialisation has focused on the issue of engagement with business, government and civil society (Gianelle et al., 2017), on the capacity of business and regional and local government to clearly prioritize needs and opportunities (Vivanco et al., 2016), on patterns of regional diversification (Balland et al., 2016) and on the challenges to implementation in less developed regions (Lazzaretti and Innocenti, 2016).

The magnitude of the financial resources mobilized by the Smart Specialisation strategy as well as its spatial and thematic extent make it particularly urgent to fill the substantial gap in the policy knowledge basis. If it too early for any credible counterfactual assessment of the impacts (and their conditioning factors) of Smart Specialization measures, it is still possible to look into the copious experience accumulated over previous programming periods in order to identify suitable programmes anticipating (at least some of) the features of the 'new' programmes inspired by th Smart Specialisation approach. A policy learning exercise aimed at extrapolating out from a particular case in order to draw some (at least tentative) conclusions and guidance for ongoing-policies .

3. The Collaborative Industrial Research (CIR) program

The Collaborative Industrial Research (CIR) is a scheme of the *National Program for Research and Competitiveness* (henceforth PON R&C), funded during the 2007-2013 EU Cohesion Policy programming period by the European Regional Development Fund (ERDF) jointly with national sources (the co-financing share plus additional resources devoted to research activities from the Research facilitation fund- FAR). The budget - roughly 1 billion euro - is intended to subsidize *industrial research* projects, undertaken by firms located in the Italian less developed regions (Calabria, Campania, Puglia and Sicilia; that is, the regions included in the convergence objective for the 2007-13 programming cycle). In what follows, we sketch the feature of the CIR most relevant for our empirical investigation. Additional information can be retrieved from the PON R&C web site.
CIR is a competitive fundingscheme coordinated by a national strategic coordination unit and activated by local stakeholders in collaboration within each other (demand-driven policy). Firms apply for funding made available by the program by submitting detailed project applicatons premised on the identification of their own priorities and collaboration strategies with other firms and other research-active stakeholders. The program aims to foster both public and private R&D by means of the interactions between direct grants to universities and R&D subsidies to private firms.
CIR is, therefore, an ideal case study of a program anticipating some of the characteristics introduced in many innovation policies implemented in the 2014-20 period under the S3 framework.

In particular: i) only projects that fall clearly in one of the priority areas identified by the programme are eligible for funding (concentration of resources); ii) CIR applicants should identify and justify their own context-specific priorities within a set of pre-selected highly-innovative activities entitled to receive funding (i.e. ICT; Advanced materials; Energy and energy saving; Health and biotechnology; Agro-industrial system; Aerospace and aeronautics; Cultural heritage; Transport and advanced logistics; Environment and safety. A full list of the eligible activities is provided in Annex 1) (Bottom-up selection of local priorities among a set of centrally identified areas of activity); iii) CIR applicants should also identify ex-ante their collaboration strategy, with the CIR guidelines dictating that each project should be submitted by multiple firms and that consortia that also include research centers will be favored in the selection process (collaborative dimension).
The CIR was launched in January 2010 by means of an open call issued by the Managing Authority of the PON R&C inviting firms to submit industrial research projects to be financed by the scheme. By the end of April 2010 (submission deadline), 533 applications were submitted, for a total amount of requested subsidies of approximately 6 billion euros. Applications involved approximately 1,000 entities (firms, research centres and/or universities). The evaluation of the funding applications by panels of independent experts[3] took place in May and June 2010. Applications were evaluated in light of their expected economic returns by means of a three steps evaluation procedure. The call for applications specified that a key selection criteria for the successful projects was the assessment by the selection panel of the expected impacts on industrial competitiveness of the development and implementation of the new technologies proposed in the application. In May 2010 the ranking of the applications was released. A single score was assigned to each application project ranging between 20.48 and 138.17. All project applications scoring below 96 were deemed not eligible for financing by the call for applications. The remaining eligible proposals (196 in total) were funded subject to budget availability following their rank order. Given the available budget and the total funding requested by each project, only projects that received a score above 104.4 were in fact funded, whereas some eligible projects did not receive any funding due to the lack of sufficient funding (32 projects received no subsides, notwithstanding their eligibility granted by a score above 96). 143 large enterprises, 229 SMEs, 167 Micro Enterprises, 237 Universities and 161 research entities received funding. The average value of the financed projects was roughly 9 million euro, with an average subsidy of roughly 6 million euro.

Funded projects were mandated to start the proposed activities as soon as possible following the announcement of the results and to conclude the entire project in a maximum of three years from the start date. In order to strictly enforce these requirements, projects could benefited from an upfront transfer of up to 75% of the total funding conditional on having started the project by October 30th 2011. It is also important to stress that projects receiving funding under the CIR

[3] After the preliminary check of formal validity in charge of the dedicated ministerial office, 9 thematic panels of technical-scientific experts (one panel for each activity) evaluated the projects attributing them a score. Then, an additional final evaluation was made by another independent committee who acquired the opinion of the experts and attributes to the projects an additional score according to the results of the controls of the physical locations where the activities would have been carried out.

programme cannot receive any funding from any other source. This makes it possible to exclude a priori any additional confounding source of funding at the time of the application as well as for the entire duration of the project. Unfortunately, the same conditions do not apply to the projects that did not receive funding. In order to mitigate any confounding factor, we checked in the OpenCoesione[4] dataset whether firms applying for projects not financed received any other form of EU funding from 2012 onwards and we excluded from our analysis all firms that received other forms of funding.[5]

4. Data

All data related to the CIR are taken from its official database (named SIRIO). For each project the database includes the evaluation score as well as a wide set of characteristics, among which the tax code of the participating firms. The firms' tax code has allowed us to merge the CIR dataset with firm balance-sheet information from CERVED (a database with firm-level budget data), employment data from INPS (National Institute for Social Security), patent data from ORBIS (firm-level database provided by Bureau van Dijk merged with OECD Patstat) as well as additional project-level data from OpenCoesione. The analysis is focused on firm-level data (balance-sheet data for research centers or universities – mostly public Italy - are not easily available and not comparable with private companies). Each firm can in principle participate in more than one funded project (while firms participating in both a subsidized and unsubsidized project are removed from the analysis). In order to account for the heterogeneous start dates of the projects, we consider as outcomes yearly averages (referring to the time span firms have actually received funding). The variables used in the empirical analysis are listed in Annex 2.

5. Empirical analysis and identification strategy

The empirical analysis aims to evaluate whether the receipt of CIR subsidies makes a difference to the firms' performance. As discussed above, subsidies were granted according to the scoring assigned by the independent evaluators: only the projects that received a score above the cutoff of 104.4 were actually funded. We exploit this discontinuity to investigate the causal impact of the CIR scheme on firm performance. In principle, projects ranked differently may differ in terms of many observed and unobserved characteristics that can be correlated with measures firm performance. For instance, highly scored projects might be of superior intrinsic quality and, therefore, they might not face any credit constraint that would prevent their implementation even in absence of the

[4] OpenCoesione is the Italian governmental portal which collects data on all the single subsidies co-financed by EU money and those one financed by National resources in Italy. This represents the overwhelming majority of the subsidies available for firms located in convergence regions.

[5] The control leads us to a reduction of 40 percent of the initial sample (we kept 1,172 observations of the 2,078 observations that we have by matching the CIR database with the CERVED database. The composition among treated - 11 percent - and non-treated remains comparable).

funding. By applying a regression discontinuity design (RDD), we are able to differentiate out all the characteristics of the projects that may confound the identification of the causal effect of the scheme. The key intuition behind this research design (Angrist & Lavy, 1999; Black, 1999; Van Der Klaauw, 2002) is that projects just below the cutoff (non-financed) make a suitable good comparisons group for those just above the cutoff (financed). This strategy is deemed preferable to other non-experimental methods because if the units of analysis are unable to manipulate precisely the forcing variable (the ranking), the variation in treatment around the threshold is randomized as if the projects had been randomly drawn just below or just above the threshold (see Lee, 2008).

One implication of the local randomized result is that the empirical validity of the RDD can be empirically tested. If the variation in the treatment near the threshold is approximately randomized, it follows that all "baseline covariates" – those variables determined prior to the realization of the forcing variable (the score) – should have about the same distribution just above and just below the cutoff. Section 6 presents a test for the absence of discontinuity in baseline characteristics around the threshold that substantiates the empirical strategy. The causal effect of the CIR is assessed by allowing the outcome variable to be a function of the score and testing the existence of a discontinuity in the intercept at the threshold. The forcing variable is centered at the cut-off value. In order not to impose any restrictions on the underlying conditional mean functions, the polynomial function of the centered score is interacted with the treatment dummy (Angrist and Pischke, 2011). The specification is the following:

$$Y_{ijt} = \alpha + f\left(score_{ij}\right) + T_{ij}[\beta_1 + f\left(score_{ij}\right)] + \varepsilon_{ijt} \qquad (1)$$

Where *i* is the firm; *j* is the project; *t* the time period (2011-2014) and the standard errors are robust to heteroschedasticity and clustered at the project level (Lee and Card, 2008). In the main specification models are estimated by following Athey and Imbens (2016) i.e. within the optimal bandwidth and with the optimal polynomial degree (Calonico et al., 2014). As for robustness checks purposes, models are estimated also with a global polynomial function of up to degree 3 with the AIC criterion selecting the best specification. We also provide estimation results to check for the presence of heterogeneous impacts at the threshold. In this case (as in Becker at al., 2013 and Accetturo et al., 2014), we will add to equation (1) an additional forcing variable (Z) that accounts for the conditioning aspect under investigation.

$$Y_{ijt} = \alpha + f\left(score_{ij}\right) + g\left(Z_{ij}\right) + T_{ij}\left[\beta_1 + f\left(score_{ij}\right) + g\left(Z_{ij}\right)\right] + \varepsilon_{ijt} \quad (2)$$

Note that while our identification strategy delivers a highly credible picture of the effect of the subsidy for the subpopulation of firms close to the threshold, for those further away, the RDD results may be less informative. This is unfortunate because in our case identification away of the cutoff is particularly relevant: policy makers might want to know what might have happened if firms with scores below the threshold would have gained access to the scheme; by the same token, they might wonder whether the public money spent for the firms that easily pass the admission threshold carry with it deadweight losses. To gain some insights in this regard, we make use of the Angrist and Rokkanen (2015) conditional independence assumption (CIA). CIA breaks the relationship between treatment status and outcomes by means of a vector of covariates such that, conditional on it, outcomes are (mean) independent of the running variable. The vector of covariates is then used to identify counterfactual values for the outcome variables of interest away from the cutoff.

6. Empirical findings

In this section we first document our baseline RDD results at the 104.4 cutoff. Subsequently, we substantiate the validity of our RDD identification strategy by looking at manipulation, balancing and placebos. Next, we search for interesting asymmetries at the threshold, which might clarify the mechanisms at work. Finally, we provide the extrapolations away from the cutoff.

Baseline

Table 1 reports our baseline results. We consider three outcome variables: investment, value added and number of Employees. All of them are specified as logarithmic growth rate (over the 2011-2014 period) standardized with respect to the initial (2010) size of the balance sheet.[6] Our variable 'Investment' includes both tangible and intangible capital outlays, as the CIR does not discriminate between the two. We sum up all investments undertaken by each firm. Estimates are derived from a nonparametric estimator, where the optimal bandwidth and the polynomial degree according to which the models are estimated are selected by the routine robust (Calonico et al., 2014; Athey and Imbens, 2016). The results reported in the table suggest that the impact at the threshold is negative and generally not significant (borderline statistical significance is found for Value Added).

[Table 1]

As a preliminary robustness check, we want to verify that these results continue to hold for different specifications. Table 2 reports those from parametric (global higher order polynomial approximations) regressions. The impact at the threshold is estimated by considering the forcing variable with the degree of polynomial (f) allowed to vary differently on the two sides of the threshold, interacted with the treatment dummy and selected by the Akaike Information Criterion (AIC). The AIC suggests that the best degree of the polynomial approximations are (1-1), (3-1), and (3-1), respectively for the three outcomes. These additional results confirm those reported in Table 1, with a non-significant impact of the CIR for all outcomes. Figure 1 illustrates the classical RDD figure for the outcome Investment in the AIC preferred specification, where the threshold is normalized to zero for convenience.

[6] This is the standard specification in the literature (see, for instance, Bronzini and Iachini, 2014). However, to test robustness, we check for alternative specifications of the outcomes variables. In particular, we specified them as relative variation and using the variation only between 2010 and 2014, with qualitatively similar results.

[Table 2]

[Figure 1]

Testing the validity of the identification framework.

The RDD framework relies on the fact that firms cannot manipulate their ranking in order to get funding. In our case this requirement seems to be trivially verified, as the score is assigned by the panel of independent experts. In any case, we investigate the smoothness of our forcing variable (the score) around the threshold. Figure 2 plots the density of firms (using bin sizes equal to 10). A visual inspection shows no increase in the probability mass after the threshold,. At any rate, the hypothesis of non-random sorting around the cutoff is rejected on the basis of the test developed by McCrary (2008).

[Figure 2]

To test the assumption that the assignment of the treatment near the cutoff is approximately randomized, we examine whether the observed baseline covariates are locally balanced on either side of the cutoff. The regression discontinuity framework provides a natural framework to check whether some confounding factor is driving some spurious correlation. It suffices to run RDD regressions (of the type in equation (1)) using as dependent variables those factors that the researcher suspects might be driving the results. If no effect is detected then that variable can be considered as controlled for in the RDD exercise. We focus on a long list of firm and project characteristics: from balance sheet data we focus on tangible and intangible capital, indicators of cash flow and of the liability side of the balance sheet, which proxy for credit constraints, traditional proxies for profitability, labor and service costs and the number of employees (from INPS). We test also the project and firm features that capture the S3 elements, such as the nature and the dimension of the project's partnership (presence of a University, number of the subjects collaborating), the activity of the project, the economic sectors of the firms, its innovative capacities and its internationalization. These variables will be used below to check for heterogeneous effects at the threshold. The results (which are derived from the same specification as in Table 1) are shown in Table 3. No jump occurs at the threshold for most of the baseline covariates. Exceptions refer to the Return On Assets (ROA). As explained by Lee and Lemieux (2010), some of the differences in covariates across the threshold might be statistically significant by random chance. To check for this possibility, we combine the multiple tests into a single test statistic that measures whether data are broadly consistent with the random treatment hypothesis around the cutoff. We carry out a χ^2test for discontinuity gaps by estimating Seemingly Unrelated Regressions (SUR), where each equation represents a different baseline covariate. In none of the equations is there any evidence of discontinuities.[7]

[Table 3]

[7] Results are available from the authors.

Table 4 documents some of the experiments we have run to further test the robustness of our results. We show coefficients from placebo experiments, estimating the impact of the CIR on Investments, Value Added and Employment where no treatment takes place. We document the results obtained by using respectively a fictitious threshold (we use 94.4, instead of the actual 104.4) and a fictitious time-window (we maintain the true cutoff and verify what happens in the pre-treatment period 2008-10, rather than the post-intervention period). Should these placebos provide statistically significant results, the comparability between treated and controls units in our sample might be at jeopardy. Reassuringly, the results are very supportive, except for the coefficient on Employment when a mock threshold is used. This finding (which however does not show up when different fake thresholds are used) signals that the evidence on CIR employment impacts might be less robust when compared to those on Investment and Value Added.

[Table 4]

Heterogeneity at the threshold.
We move next to check whether our results at the border show any discernable asymmetries. In particular we are interested in the S3 forerunner characteristics of CIR. Table 5 shows the results obtained by estimating equation (2) with reference to six additional forcing variables, those indexed by Z_k (with k from 1 to 6). Preliminarily, it should be noted that the variables Z_k are continuous at the 104.4 threshold, as shown in Table 3. Therefore the estimation of Eq. (2) is a feasible exercise (Becker et al., 2013 and Accetturo et al., 2014). It is worth noticing, that the findings reported in Table 5 should be interpreted with care, as the additional forcing variables Z_k might be cross-correlated. Moreover, some of them might be endogenous to the scheme. For instance, knowing that the inclusion of an academic partner raises the CIR score, might have induced participants to include universities in their applications in order to maximize their probability of receiving the grants, with limited interest in actual collaborations.

[Table 5]

The investigation of the CIR mechanisms that more directly anticipated some of the features of the programmes inspired by the S3 approach leads to the following evidence. The presence of a University (Z1) in the application seems to have had a positive effect (marginally significant) on employment levels. On the other hand, collaboration (Z2) per se does not seem to add to the overall impact of the scheme. On average, the projects that included a large number of firms (i.e. projects with more than 13 partners among firms and Universities) perform relatively worse (the negative interactions enter highly significantly when the outcomes are Value Added and Employment). As for the innovative nature of the activities supported by the scheme, we consider those that can be classified as advanced in terms of knowledge intensity and technological capabilities. In particular, we identify CIR projects in the activity areas: ICT, Advanced materials, Health and biotechnologies and Aerospace and aeronautics (Z3). We do not find that these projects use funds more effectively, compared to other – more traditional - areas of activity (i.e. Energy and energy reduction, Agro-industrial system, Cultural heritage, Transport and advanced logistics, Environment and safety).

Looking at the characteristics of the beneficiary firms, the empirical evidence suggests that the scheme has benefited relatively more firms operating in low tech sectors (Z4) (as to the Eurostat/OECD classifications[8]). These firms are those facing stronger constraints in terms of access to credit as well as those for which collaboration with more innovative counterparts might offer the highest returns. The results for firms with a high ex-ante patenting track record (Z5) are instead less straightforward: the impact on investment is negative and highly significant, while Value Added seems to have been positively influenced by the subsidies. This evidence is probably capturing the life-cycle of innovative activities: firms can take full advantage of CIR incentives in terms of innovation output (measured by value added) when their stock of knowledge (existing patents) is already formed. In this case, CIR incentives are used to capitalize on the potential of previous investments (by increasing sales, for instance) rather than to support further investment. Finally, program effectiveness has been limited for multinational corporations (Z6), suggesting that to in order to maximise returns to innovative investment S3 programmes would need to find the right approach to take into account the specificities of these firms and mobilize their potential. Even if domestic/small medium enterprises (SMEs) can certainly play an important role in innovation processes the key innovation players remain large and often multinational firms.

Far-from-the-threshold extrapolations.

The results discussed so far are valid only for firms very close to the funding cutoff. By using the Angrist and Rokkanen (2015)'s CIA we are able to analyses the impact of the CIR far from the threshold. This is equivalent to explore what might have happened with a more stringent (or more generous) funding threshold. As discussed in Section. 5, the possibility to extrapolate the impact of CIR for firms distant from the cutoff relies on breaking the relationship between treatment status and outcomes by means of a vector of covariates such that, conditional on it, outcomes are (mean) independent of the running variable.

To ensure that the relationship between the running variable and the outcomes has been removed, we run for each outcome CIA tests from estimation windows of various width. The CIA test come from models that control for Tangible and Intangible Capital, Value Added, Total balance sheet, Cash flow, Labor Cost, Service Cost, and Employees (all of them measured in 2010, before the launch of the program). The results show that for both Investment and Value Added the CIA is violated starting for the smallest bandwidth used (15 score points on the two sides of the financing cutoff). Therefore, for these two outcomes we are not able to provide far-from-the-threshold extrapolations. On the other hand, for the outcome Employment and up to the bandwidth of [-32, +32] score points we fail to find any sign of CIA violations (see Table 6). Therefore, limited to Employment we are able to provide far-from-the-threshold inference for up to the 30% of the observations in our sample. The results suggest that a more (or less) generous level funding of the scheme would have not

[8] www.ec.europa.eu/eurostat/

affected programm effectiveness. The CIA extrapolations for employment on the right of the cutoff are depicted in Figure 3.

[Table 6]

[Figure 3]

7. Conclusions

This paper has investigated the impact of CIR - a programme designed to foster industrial innovation in less developed regions of the Italian Mezzogiorno. The analysis of this forerunner program offers relevant insights to inform the design and implementation of programmes inspired by the S3 approach in the 2014-20 programming cycle and offers material for evidence-based reflections on post-2020 EU policies.

The results suggest that the impact of CIR on firm performance has been limited in terms of additional investments, value added and employment. This first key insight calls for a cautious approach to the reform of innovation policies. The simultaneous introduction of new features, conditionalities and requirements in innovation programmes might be a risky choice. A gradual and evidence-based approach to policy reforms might be the best approach until robust evidence is produced on the impact and value added of alternative policy options.

The analysis of the influence of specific features of CIR that might be relevant to the implementation of 'new generation' programmes inspired by the S3 approach unveiled a number of relevant insights on how to improve the performance of existing schemes.

Collaboration is an increasingly important feature of all innovative activities (Crescenzi et al., 2016) and S3 has created the pre-conditions for the development of policy tools aimed at the reinforcing the collaborative dimension of innovation policies. However, when collaborations are not the results of an open and unconstrained search for the best possible partners but – on the contrary - are induced by public policy incentives they fail to generate positive impacts. Collaborations with universities have offered limited benefits to partner firms but also collaborations with other private firms have generated no impact on the effectiveness of CIR. Moreover, very large partnerships have proven highly dysfunctional leading to negative impacts on firm performance. In light of this evidence policy makers should consider very carefully the practical tools leveraged by the various S3 programmes in order to foster collaboration. Collaboration should reflect the genuine needs of local innovation agents and single-applicant submissions might be the best option in some cases. Therefore, the collaborative dimension of S3 projects should not be a requirement to be 'rewarded' as such but should supported only where a clear rationale is provided in light of the specific technological problem that the applicant intend to solve.

The pre-selection of high knowledge intensity areas of activity has also failed to deliver the intended benefits when compared to more traditional technological domains. Again this calls for a broad approach to innovation policies to be based on careful diagnoses of the features of the regional economy. Where more traditional technological domains are a source of competitive advantage, policy makers should not signal any preference in the allocation of funding in favour of more advanced sectors. On the contrary, at the moment many EU less developed regions – irrespective of their initial conditions - have submitted their S3 operational programmes placing a strong emphasis on advanced technological domains in an attempt to maximize their chances to receive funding for their 'smart' choices (see data from: S3platform.jrc.ec.europa.eu/).

The capability of firms to benefit from S3 is likely to be heterogeneous. The analysis of CIR suggests that firms active in low-tech sectors are those more likely to benefit from S3-style support to their innovation activities. These firms face more difficulties in accessing credit to fund their innovation projects. In this context CIR has addressed a clear market failure allowing them to expand their investment and foster their collaborations. Based on this evidence S3 strategies might offer relevant opportunities to firms in traditional sector. This calls for more attention in less developed regions for balanced S3 strategies. Low tech sectors might be a less flashy but more rewarding target for public resources. Innovative firms – as measured by their patent stock – (irrespective of their sector of activity) might benefit from policies inspired by S3 principles but displacement effects of private investments are to be expected and additional impacts are likely to remain limited to the exploitation and commercialization of existing ideas. Impacts on multinational internalized firms are absent. The complexity of the scheme with its collaborative requirements - by increasing transaction and coordination costs – reduces the returns for complex internally diversified organisations. In light of this evidence the mobilization of larger firms remains a challenge for current and future S3 strategies that should be carefully considered.

These findings provide some initial evidence-based insights to inform and reinforce the debate on the S3 approach and its future post-2020, within the informative boundaries (and limitations) imposed by the methodology. For instance, external validity is a fundamental challenge and our results based on the experience of the less developed regions of Italy during the years of the Great Recession may not be immediately applicable to other EU regions under less extreme circumstances. Therefore, the results of this paper call for the investigation of further case studies in different EU countries by means of robust counterfactual evaluation methods. The impacts of current S3 programmes will not unfold early enough for their evaluation to inform evidence-based debates. The rigorous analysis of forerunner programmes might be the only feasible approach to the development of evidence to inform key decisions on the future of EU Policies after 2020.

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Table 1. The impact of the CIR on Investments, Value Added and Employment (non-parametric results)

	Investments	Value Added	Employment
Treatment	-0.9572	-1.0903*	-0.2213
	(0.7053)	(0.5156)	(0.5841)
Constant	-2.8617***	-1.0051**	-5.4239***
	(0.5862)	(0.3655)	(0.3446)
R squared	0.0213	0.0858	0.107
Polynomial degree	1	1	1
Observations	105	67	66

Notes: Standard errors (in parenthesis) are clustered at the project level. Estimates derived with the optimal bandwidth and the polynomial degree selected by the routine robust (Calonico et al., 2014).
Significance level: ***<0.001; **<0.010; *<0.050.

Table 2. The impact of the CIR on Investments, Value Added and Employment (parametric results)

	Investments	Value Added	Employment
Treatment	-0.0295	-0.4122	-0.3818
	(0.3545)	(0.3077)	(0.3429)
Constant	-3.5173***	-1.1167***	-5.1670***
	(0.1763)	(0.2565)	(0.2975)
R squared	0.002	0.007	0.005
Polynomial degree	1-1	3-1	3-1
Observations	909	925	933

Notes: Standard errors (in parenthesis) are clustered at the project level. Estimates derived with global higher order polynomial approximations where the polynomial degree is selected, separately for each side of the cutoff, by the AIC. Significance level: ***<0.001; **<0.010; *<0.050.

Table 3. Balancing for the baseline covariates

	Treatment	Obs	R sq
Tangible Capital	0.0136 (0.0081)	103	0.0193
Intangible Capital	0.0103 (0.0073)	99	0.0119
Value Added	9890.526 (5873.65)	105	0.0253
Sales	52340.63 (35227.32)	103	0.0299
Total balance sheet	55381.84 (28109.31)	105	0.0209
ROA	-5.5281* (2.6408)	104	0.0577
ROE	0.0003 (0.0003)	102	0.0288
Cash Flow	2812.833 (2378.991)	105	0.0368
Consolidated debt	0.0143 (0.0119)	71	0.0177
Labour Cost	5635.963 (3398.668)	99	0.0207
Service Cost	17976.27 (11717.51)	105	0.0284
Employees	0.0006 (0.0003)	54	0.1670
Project with a University	0.4550 (0.2407)	105	0.1339
Project in advanced activities	0.1393 (0.2798)	105	0.0453
Project with low tech firms	0.2253 (0.1824)	105	0.0921
Project with patenting firms	-0.6956 (1.5266)	105	0.0522
Project of large consortium	0.4187 (0.2330)	105	0.0778
Project with multinational firms	0.0530 (0.0547)	105	0.0319

Notes: We reported here the results estimated according to the sample identified in column 1 of Table (1). Standard errors (in parenthesis) are clustered at the project level. The variables are measured in the pre-treatment year. Significance level: ***<0.001; **<0.010; *<0.050.

Table 4. Placebo experiments

	Investments	Value Added	Employment
		Mock threshold	
Treatment	-1.9116	-0.4039	-3.1445**
	(1.0909)	(1.2644)	(1.0671)
Constant	-1.8058	-0.9870	-2.6214**
	(1.0270)	(0.1453)	(0.9102)
R squared	0.046	0.023	0.160
Observations	105	67	66
		Pre-treatment period	
Treatment	0.5417	-0.0961	0.28630
	(0.6757)	(0.4923)	(0.6496)
Constant	-3.4501***	-1.1023***	-5.3252***
	(0.5682)	(0.2723)	(0.3344)
R squared	0.066	0.053	0.122
Observations	105	67	66

Notes: Same specification as in Table (1). Standard errors (in parenthesis) are clustered at the project level. Significance level: ***<0.001; **<0.010; *<0.050.

Table 5. Heterogeneity at the threshold

		Investments	Value Added	Employment
Z1: **Public research** (presence of a University in the project partnership)	Treatment	-0.1453	-1.6309	-1.0830
		(0.9740)	(0.8394)	(0.6305)
	Z1	0.6483	0.4601	-0.5239
		(0.7095)	(0.4736)	(0.3017)
	Treatment*Z1	-1.1480	0.4142	1.0767*
		(0.8926)	(0.7503)	(0.4205)
	P Wald Test	0.190	0.0952	0.0671
	R squared	0.0345	0.133	0.128
	Observations	105	67	66
Z2: **Collaboration** (project partnership involving large number of firms)	Treatment	-0.8257	-0.5536	0.4983
		(0.8022)	(0.5951)	(0.6472)
	Z2	0.4890	1.1821**	1.0165**
		(0.2533)	(0.4141)	(0.3181)
	Treatment*Z2	-0.5514	**-1.9874*** **	**-1.9942*** **
		(0.5438)	**(0.5263)**	**(0.4992)**
	P Wald Test	0.0323	0.0000	0.0004
	R squared	0.028	0.258	0.268
	Observations	105	67	66
Z3: **Activities** (activity of the project classified as advanced)	Treatment	-0.7342	-1.0119	0.2194
		(0.8483)	(0.5909)	(0.6722)
	Z3	-0.1317	0.1623	1.1249*
		(0.6254)	(0.3259)	(0.4186)
	Treatment*Z3	-0.4083	-0.2672	-1.4622*
		(0.4439)	(0.4907)	(0.5910)
	P Wald Test	0.3730	0.1402	0.0632
	R squared	0.038	0.088	0.192
	Observations	105	67	66
Z4: **Low tech** (firms operating in low tech sectors)	Treatment	-1.2547	-1.0107	-0.2179
		(0.7253)	(0.5458)	(0.6059)
	Z4	-0.2369	-0.5737*	-1.6071***
		(0.2933)	(0.2650)	(0.2222)
	Treatment*Z4	**1.2951** **	0.1203	**1.3514** **
		(0.4333)	(0.4162)	**(0.4749)**
	P Wald Test	0.0121	0.0072	0.0000
	R squared	0.065	0.107	0.139
	Observations	105	67	66
Z5: **Patenting** (firms with a high capacity of patenting)	Treatment	-0.8859	-1.2257*	-0.3824
		(0.6939)	(0.5449)	(0.5857)
	Z5	0.1774***	-0.1124*	-0.0683**
		(0.0465)	(0.0476)	(0.0259)
	Treatment*Z5	**-0.1697*** **	**0.2223*** **	0.1248
		(0.0477)	**(0.0596)**	(0.0876)
	P Wald Test	0.0000	0.0054	0.0730
	R squared	0.031	0.110	0.138
	Observations	105	67	66
Z6: **Internationalizion** (multinational corporations)	Treatment	0.8960	-1.3914**	-0.4506
		(0.7070)	(0.4655)	(0.5474)
	Z6	-0.2511	1.8244***	1.3255***
		(0.5401)	(0.3209)	(0.2883)
	Treatment*Z6	-0.7148	**-0.9529***	**-1.7699***
		(0.6535)	**(0.3698)**	**(0.7928)**
	P Wald Test	0.0225	0.0000	0.0005
	R squared	0.048	0.245	0.186

Observations	105	67	66

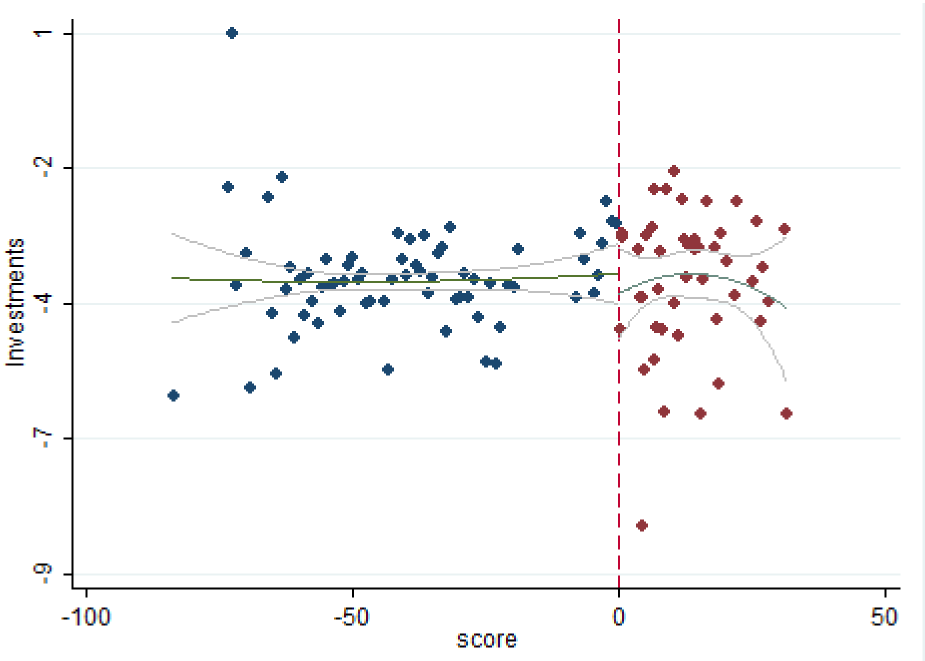
Notes: Same specification as in Table (1). Standard errors (in parenthesis) are clustered at the project level. Significance level: ***<0.001; **<0.010; *<0.050.

Table 6. CIA-based estimates. Conditional Independence test

		Employment
[- 32, 32]	Below the threshold	0.0090
		(0.0083)
	Observations	173
	Above the threshold	0.0031
		(0.0177)
	Observations	93
[- 25, 25]	Below the threshold	0.0286
		(0.0153)
	Observations	82
	Above the threshold	0.0039
		(0.0199)
	Observations	86
[- 15, 15]	Below the threshold	0.0029
		(0.0536)
	Observations	45
	Above the threshold	0.0264
		(0.0251)
	Observations	61

Notes: Regression based tests of the conditional independence assumption. The table reports the estimated coefficient of the running variable. Estimates use only observations below or above the threshold and were computed in the forcing variable window indicated in the first column. Standard errors are in parenthesis. Significance level: ***<0.001; **<0.010; *<0.050.

Figure 1. The impact of the CIR on Investments



Notes: Quadratic polynomial relations. Each point represents the average Investments variation. Treated side is in red color (right part of the graph).

Figure 2. Firm density around the cutoff

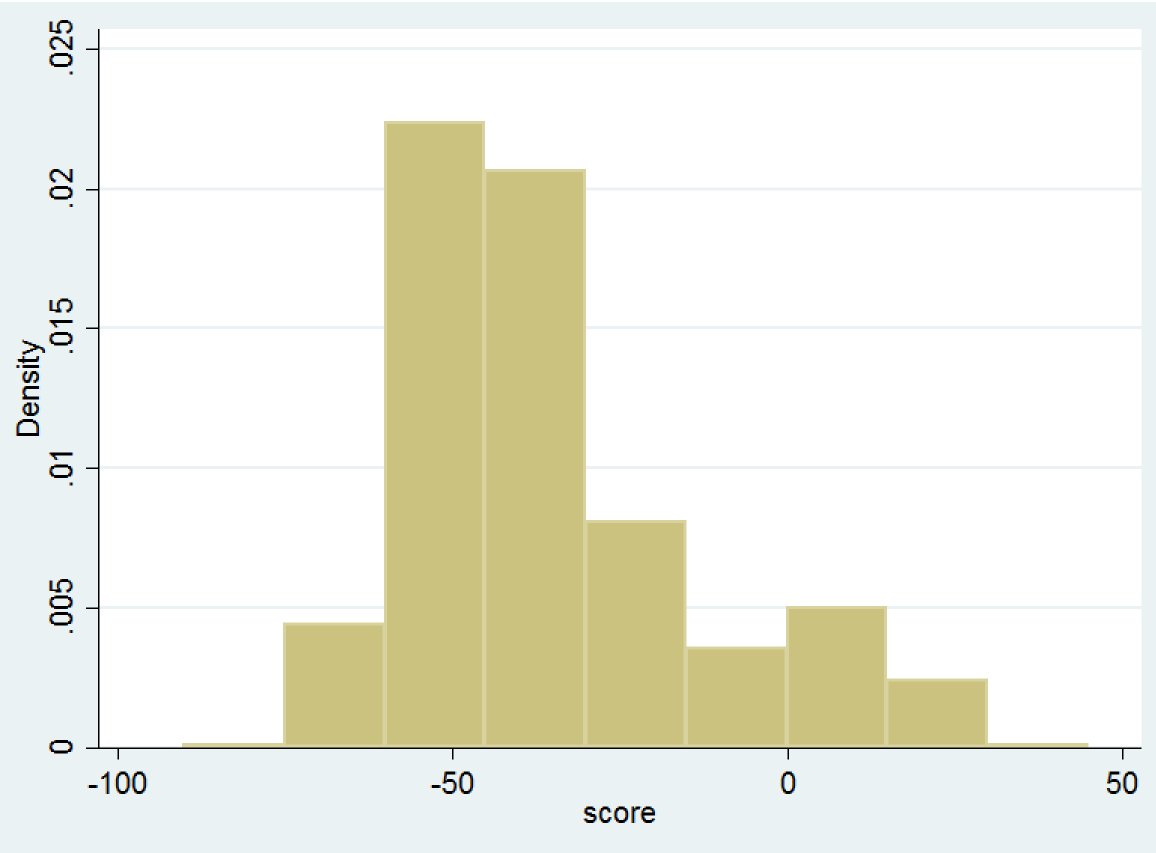
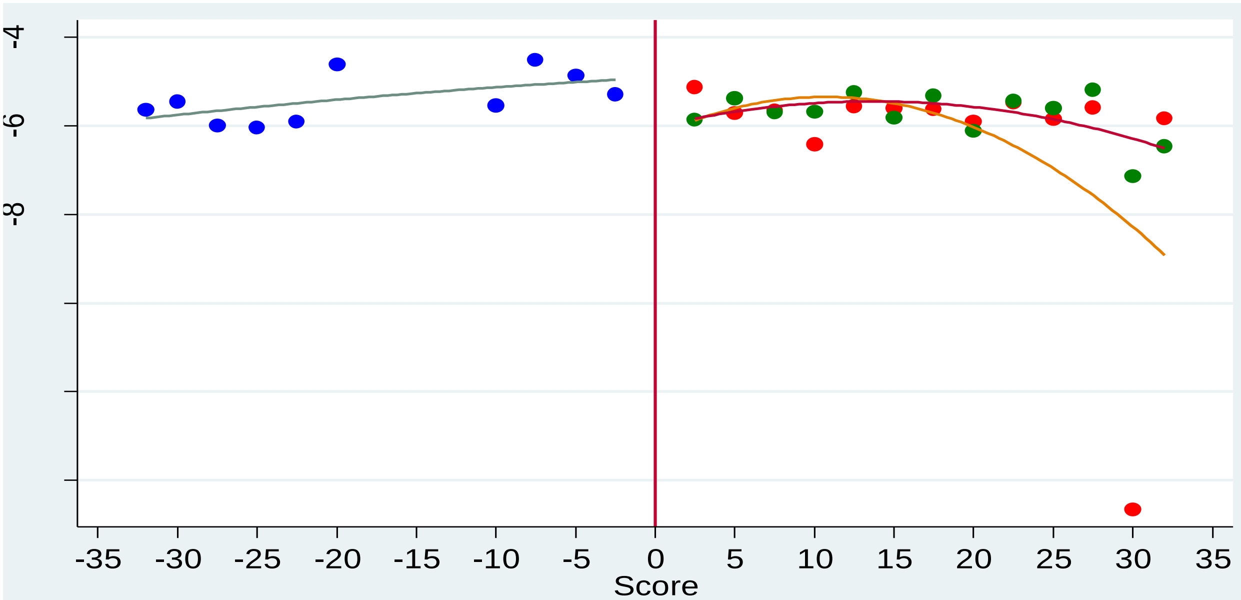


Fig. 3 CIA based estimates, Employment



Notes: graphical representation of CIA-based estimates (Angrist and Rokkanen, 2015). The extrapolations are computed through Kline's linear reweighting procedure (Kline, 2011). The fitted values for observed outcomes are represented by the blue (on the left of the cutoff) and the green (on the right of the cutoff) dots. On the right of the cutoff red dots are represent the CIA-based extrapolations.

Annex 1 – CIR

With Directorial Decree (D.D.) No. 1/Ric. of 18 January 2010 and by means of an open invitation, the Collaborative Industrial Research (CIR) Program has selected highly scientific and technological projects capable of innovating business products, procedures and services. The objective is to make the Convergence regions (Puglia, Sicily, Calabria and Campania) more competitive by promoting the sustainable development of these areas, diversifying production specialization and strengthening sectors of excellence. A decisive factor in the selection of the projects was the demonstration of how the implementation and development of these enabling technologies would improve industry competitiveness and quality of life. Projects could have been presented for 9 scientific and technological areas, which the CIR believed to be strategic. This is the complete list:

1) ICT;
2) Advanced materials;
3) Energy and energy saving;
4) Health and biotechnology;
5) Agro-industrial system;
6) Aerospace and aeronautics;
7) Cultural heritage;
8) Transport and advanced logistics;
9) Environment and safety.

CIR Website: http://www.ponrec.it/en/programme/measures/industrial-research/

Annex 2 – Variables for the empirical analysis

Variable	Description and Source	Mean	Std. Dev.	Min	Max
		Outcome variables			
Investments	Variation of tangible and intangible capital (Log Average annual growth rate 2011-2014) CERVED	-3.5689	1.6868	-10.8526	2.4734
Value Added	Total Value added (Log Average annual growth rate 2011-2014) CERVED	-1.6094	1.1656	-7.2626	2.4772
Employment	Number of employees (Log Average annual growth rate 2011-2014) INPS	-5.6376	1.1970	-10.0820	-0.7701
		Treatment variables			
Project id	CIR – OpenCoesione	-	-	-	-
Partner id	CIR – CERVED – INPS – ORBIS - OpenCoesione	-	-	-	-
Score	Score attributed to the project by the CIR ranking. The score of the project *j* is valid for all the partners *i*. CIR	-36.3497	21.3241	-83.92	31.49999
Treatment	Dummy =1 for partner *i* of the project *j* with a score >104.4 CIR	0.0947	0. 2929	0	1
		Conditioning variables			
Z1	Project partnership involving a University CIR	0.9138	0.2807	0	1
Z2	Project partnership involving more than 13 partners CIR	0.5367	0.4989	0	1
Z3	Project belonging to the activities: ICT, Advanced materials, Health and biotechnologies and Aerospace and aeronautics CIR	0.3626	0.4810	0	1
Z4	Partners of the project operating in a low tech sector (according to the Eurostat-OECD classification) CERVED	0.1207	0.3259	0	1
Z5	Partners of the project with a high capacity of patenting (number of registered patents) ORBIS	1.4504	18.21198	0	560
Z6	Partners of the project belonging to a multinational corporation ORBIS	0.0342	0.1817	0	1
		Other covariates			
Tangible Capital	Euro (2010) CERVED	6,251	70,991	1	2,166,715
Intangible Capital	Euro (2010) CERVED	3,482	43,341	1	1,189,502
Value Added	Euro (2010) CERVED	4,284	28,331	-344,571	511,498
Sales	Euro (2010)	16,589	85,349	1	1,538,923

	CERVED				
Total balance sheet	Euro (2010) CERVED	23,341	151,044	3	3,839,581
ROA	Return of Assets (2010) CERVED	2	18.5371	-252	95
ROE	Return of Equity (2010) CERVED	-15	217.8021	-4,927	700
Cash Flow	Euro (2010) CERVED	343	17,113	-394,748	345,722
Consolidated debt	Euro (2010) CERVED	4,942	34,574	1	578,372
Labour Cost	Euro (2010) CERVED	3,973	20,889	1	410,764
Service Cost	Euro (2010) CERVED	5,888	32,108	1	548,049
Employees	Number of Employees (2010) INPS	181	488	1	5,006