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Gaining in impacts by leveraging the policy mix: Evidence from the European Cohesion Policy in more developed regions

Enrico Cristofoletti[1] | Roberto Gabriele[1] | Mara Giua[2]

[1]Department of Economics and Management, University of Trento, Trento, Italy

[2]Department of Economics and Rossi-Doria Centre, Università degli Studi Roma Tre, Rome, Italy

Correspondence
Roberto Gabriele, Department of Economics and Management, University of Trento, Trento, Italy.
Email: roberto.gabriele@unitn.it

Abstract

This paper investigates how the overall impact of the European Cohesion Policy depends on the composition of the regional investment in *Hard* (infrastructure) and *Soft* (business and technical support) projects. The study employs a generalized propensity score (GPS) analysis in a multidimensional treatment context. In particular, the two dimensions considered are given by the *Hard* and *Soft* investments. The GPS estimation is based on a set of relevant idiosyncratic features of the regions. The second step estimates a dose–response function in a two-dimensional setting. The results confirm the existence of nonlinearities in the effect of different amounts of funds, but more importantly, show a degree of complementarity between *Hard* and *Soft* investment and that for policymakers, it is crucial to exploit such features to achieve more significant impact. The EU's more developed regions could have achieved a doubled GDP p.c. growth rate by pursuing a policy mix where *Hard* investments are reduced in favor of *Soft* investments. This improvement is comparable to the one obtained by at least doubling the available resources. The findings add to the evidence collected on the impact of the Cohesion Policy, suggesting a shift of the debate from the quantity to the quality of the expenditure pursued under the umbrella of territorial policies.

KEYWORDS

continuous multiple treatments, EU Cohesion policy, optimal policy mix, policy evaluation, regional growth

1 | INTRODUCTION

The pandemic crisis has opened the floor to a new era of the economic policy of the European Union (EU), characterized by the disbursement of an unprecedented package of financial resources to be used by the Member States (MSs) to foster the recovery of the economies hit by the pandemic. The amount of money involved in the operation is massive, with the "Next Generation EU" program (NGEU) accounting for 750 billion euros to be spent across the different EU MSs before 2023. Unfortunately, the availability of unprecedented resources is not a guarantee for NGEU to succeed.

Since its origin, Cohesion Policy has absorbed more than one-third of the EU's total budget to promote long-term competitiveness and equal opportunities to benefit from globalization to all areas and citizens. In some areas (i.e., less developed regions), Cohesion Policy resources have represented the primary source of public investment for decades, especially during the 2008 Crisis. However, the extensive literature looking at the impacts achieved by Cohesion Policy in the different programming periods and the areas/measures funded has shown how these effects are limited, heterogeneous, and driven by a series of elements, among which the total amount of available resources play only a marginal role (see Crescenzi & Giua, 2017, for a review). A consolidated role in driving the final impact is associated with the type of expenditure carried out (Di Cataldo & Monastiriotis, 2018; Crescenzi, Gagliardi, & Orrù, 2016; Rodríguez-Pose & Fratesi, 2004). Building on this evidence, we investigate if and to what extent the final aggregated achievement of Cohesion Policy in terms of economic growth (GDP) depends on how different fields of expenditure are mixed at the regional level. In particular, we focus on the conditioning role played by the composition of the regional spending in two broad categories of investments, which we labeled *Hard* (infrastructure) and *Soft* (business and technical support).

In our analysis, each region is associated with a bi-dimensional treatment whose components are the two expenditure categories. The impact of the treatment is estimated using a generalized propensity score analysis applied in a multidimensional treatment context (Egger & von Ehrlich, 2013). The method is based on two steps: first, we estimate the generalized propensity score ensuring that the balancing property is satisfied. At this stage, we identify the common support, that is, the set of regions included in the analysis for which it is possible to build a counterfactual. Secondly, we estimate the dose-response function, which provides the impacts of our bi-dimensional continuous treatment. Since the common support includes a sample of regions with characteristics typical of the more developed regions of the EU, our results cannot be extended to less developed regions. The suitability of this method for our research question is grounded on the fact that we are interested in analyzing the causal impact of a treatment that is continuous (the variability is in terms of expenditure) and multidimensional: the Cohesion Policy intervention is considered to be characterized by two broad categories of investments.

We estimate the impacts associated with the Cohesion Policy expenditure that took place at the regional level from 2007 to 2013. In addition, we simulate how the impact would have changed if there would have been an increase in available resources equal to 50% or 100%.

Results show that infrastructural investments (*Hard*) generate positive effects only if they are massive and associated with business and technical support (*Soft*), whereas *Soft* investments are always impactful. Under the constraint of the available resources, the impact in terms of GDP growth rate could have been raised from 0.8% to 1.7% by pursuing a policy mix where, on average, *Hard* investments decrease (−22.28 euro per capita) in favor of *Soft* investment (+19.37 euro per capita). In terms of shares, this would correspond to a recomposition of the policy mix from an average of 26% (*Hard*)—74% (*Soft*) to an average of 4% (*Hard*)—96% (*Soft*). The improvement such a recomposition would deliver is comparable to the one obtained by at least doubling the available resources.

The result suggests that Cohesion Policy should finance a mix of interventions where, to be protagonist, investments in infrastructures need to be accompanied by investments in business and technical support capable of reinforcing intangible assets. More generally, the paper confirms the need to overcome the debate on the funding amounts in favor of more qualitative aspects of the program.

The paper is structured as follows: Section 2 presents the background of the EU Cohesion Policy and the relevant evidence on its causal impact; by relying on existing literature, Section 3 discusses the complementarities between *Hard* and *Soft* expenditure; Section 4 presents data and descriptive statistics; Section 5 describes the methodology; Section 6 shows the results and, finally, Section 7 concludes.

2 | COHESION POLICY BACKGROUND AND CAUSAL IMPACT

Until the introduction of the Next Generation EU Program, the Cohesion Policy (together with the Common Agricultural Policy) represented the cornerstone of the economic policy of the EU.

To provide all EU regions with equal opportunities to benefit from EU integration and experience long-term competitiveness, over the recent programming periods, more than one-third of the budget of the EU was addressed to Cohesion Policy (Dijkstra et al., 2022).

Given its financial and political relevance, Cohesion Policy has been extensively studied.[1] The literature is convergent in attributing the policy's positive role in economic growth and employment (Becker et al., 2010; Pellegrini et al., 2013). Nevertheless, the impact is heterogeneous and conditioned to many aspects, among which the absorptive capacity of the regions played a propulsive role (Becker et al., 2013; Rodríguez-Pose & Garcilazo, 2015) as well as the MSs' macro-economic and institutional conditions (Crescenzi & Giua, 2020). Some evidence suggests that also the intensity of the treatment (amount of available resources) do play a role in conditioning the impact but only after overcoming a certain amount: the effect on GDP growth is not linear but strictly concave, depending on the fund's intensity (Becker et al., 2012; Cerqua & Pellegrini, 2018).

The Cohesion Policy resources are used to finance different types of projects, among which the infrastructural ones play a prominent role, especially in the earlier programming periods (Dall'erba, 2005). The emphasis on infrastructure was justified, in part, on the ground that disparities in infrastructure in the EU were greater than disparities in incomes (Martin, 1999). More recently, investments in research and development, innovation, firms support, labor market, and education also acquired primary relevance (Berkowitz et al., 2020).

Several papers focused on the impacts achieved by one or more of these different fields of interventions.

Many studies focused on the impact of infrastructural investments. By focusing on the earlier years of the Cohesion Policy, when resources were almost entirely devoted to this type of investment, Martin and Rogers (1995) advise on the detrimental role that the EU regional policy investments in infrastructures can play for the less developed areas in EU when international (vs. domestic) infrastructures are funded. The limited contribution of infrastructure to regional convergence during the early 1990s was also highlighted by De la Fuente et al. (1995) and Basile et al. (2001). In particular, it has been suggested that to be effective, infrastructure investments need to be

[1]Different empirical approaches have been proposed in this literature over the years and with respect to different focuses. Starting from (roughly) 2010, counterfactual approaches of policy evaluation dominated the existing literature, proposing results on the causal impact of the policy with respect to different outcome variables and with an increased capacity to move from the estimation of average effect to the estimation of conditioned/heterogeneous impacts. Among the other methods, regression discontinuity design (RDD) is the most employed: by exploiting the discontinuity in the treatment assignment (regions are classified as Less Developed when their GDP per capita is lower than 75% of the European GDP), this method can provide the robust and testable result on the causal impact of the policy, both in terms of average and of heterogeneous impact. Generalized propensity Score Matching has also been employed when treatment is considered continuous (e.g., expenditure) instead of binary (considering less developed regions only as treated). In all these cases, the treatment is deemed to be monodimensional. The role of the policy as a multidimensional intervention has been studied, up to now, only from a descriptive perspective rather than in a causal impact framework.

included in broad development strategies involving labor market reforms. In the presence of a low propensity for regional labor mobility and an insufficient regional wage differentiation, investments in infrastructure may only modestly contribute to the catching up of poorer regions (Basile et al., 2001). Puga (2002) reconsidered the role of regional policies in light of the location theories and, from a similar perspective, Vickerman et al. (1999) cast doubt on the ability of the trans-European Networks (TENs) to promote greater convergence in both accessibility and economic development (see also Vickerman, 2018). Crescenzi and Rodríguez-Pose (2012) depicted meager returns of infrastructure endowment on economic growth with relevant heterogeneity associated with the regional contextual conditions. The result was further investigated by Crescenzi et al. (2016), with the conclusion that the return on infrastructural investment within Cohesion Policy is influenced by the regional quality of government: in weak institutional contexts, investment in motorways—the preferred option by governments—yields significantly lower returns than the more humble secondary road. Del Bo and Florio (2012) adopted a different perspective, highlighting "the important role of infrastructure and identify the highest rates of return as associated with telecommunication, quality, and accessibility of transportation networks, with a positive impact of roads and railways" (Del Bo & Florio, 2012, p. 1393).

Several studies focused on the impact of the Cohesion Policy investments in different types of "intangibles" (e.g., firms' support, human capital, labor market, institutional capacity). Bachtrögler et al. (2020) focused on the actions aimed at fostering the competitiveness of manufacturing firms in seven EU countries, founding that they positively affect firm size (value added and employment) but not productivity. The result is confirmed by what Crescenzi et al. (2020) estimated, focusing on a specific measure of the Italian Research and Competitiveness Program (2007–2013): the positive impact involved only employment and was significant only in the low-tech sector. Causal evidence on the impact of educational measures funded within the Cohesion Policy was provided by Crescenzi et al. (2016): focusing on a learning mobility grant scheme funded by the European Social Fund in Sardinia (ex-Objective 1 region in the Italian Mezzogiorno), they conclude that learning mobility programs can reinforce skill matching only if the problem of self-selection of the beneficiaries is adequately addressed. A recent contribution has focused on Cohesion Policy projects in employment/education/inclusion concluding a positive effect of the Policy in reducing the wage gap between natives and immigrants in Italian municipalities (Giua et al., 2022).

Ferrara et al. (2017) provide a study focusing on two fields of investments (infrastructure and Research and Development), finding positive effects for both. The seminal work of Rodríguez-Pose and Fratesi (2004) analyzed the different roles played by the financial support addressed to agriculture and rural promotion; business and tourism; human capital; infrastructure, transport, and environment, pointing out the different effects that can be associated with different headings of policy.

A few papers go beyond the impacts of single fields and discuss the conditioning role played on the overall impact of different choices in terms of expenditure categories. Building on the disaggregation of expenditure proposed by Rodríguez-Pose and Fratesi (2004), Percoco (2013) studied how the different regional development strategies carried out by the EU regions are composed in terms of investment fields. The contributions of Sotiriou and Tsiapa (2015) and Albanese et al. (2021) also confirm how different types of expenditure result in heterogeneous impacts, respectively, in Greece and Italy. A qualitative analysis covering 15 EU regions leads Crescenzi et al. (2017) to conclude that beyond the specificities of each region and the heterogeneity of their local environments, the concentration of funding (in few measures within each priority axis) and effective targeting are key for the effectiveness and the overall achievement of Cohesion Policy. In particular, a reduction in concentration and the misalignment between targeted objectives and identified regional needs significantly reduce achievements. Di Cataldo and Monastiriotis (2018) further investigate the conditioning role played by the concentration of funds across various interventions and by the "alignment" between committed expenditures and measured regional "needs." By focusing on the case of the United Kingdom, they conclude that the concentration of investments on specific pillars seems to have no direct growth effects (unless regions can rely on pre-existing competitive advantages in key development areas) and that, on the other side, a significant and autonomous effect on growth is associated to the capacity of targeting investments to specific the regional needs.

The conditioning effect that the composition of the expenditure in different fields of intervention can play on the aggregated impact of the policy remained not explored in the recent literature looking at the causal impacts of the Cohesion Policy. Further research is needed to "improve policy relevance" by advising the regional responsible for the Policy on how to allocate the available resources across different fields of intervention to obtain a greater impact (Berkowitz et al., 2020, p. 64).

Going in this direction, our focus in this paper is on investigating the extent to which the aggregated impact of the Cohesion Policy depends on how infrastructures (*Hard*) and business-related—technical assistance intangibles (*Soft*) investments are combined in the expenditure pursued by the EU regions. We hypothesize that the most significant impacts are achieved if the two types of investments are complementarily activated to strengthen synergies between the different tangible and intangible growth determinants (e.g., infrastructural endowment, human capital, firms' competitiveness). Section 3 discusses the reasons why this should be the case.

3 | COMPLEMENTARITIES BETWEEN *HARD* AND *SOFT* INVESTMENTS

Infrastructural and intangible capital (business environment, human capital, knowledge, research and innovation, institutional quality) are widely recognized as determinants of growth and endogenous local development (Capello, 2015). For this reason, the development strategies pursued by the government around the world often include investments in both these fields.

As far as it concerns the return of infrastructural investments, the literature agrees on the paramount importance played by the contextual conditions of the territory where they are made. If supporting the infrastructural endowment of a region is key, as it is seen as a major factor of production able to influence the aggregate total factor productivity (Aschauer, 1989), some doubts have been raised on the direction of the relationship between infrastructures and growth (Gramlich, 1994). There is a general consensus that infrastructure per se does not have a large impact (if any) on development unless some preconditions are met (Banister & Berechman, 2001; Rodriguez-Pose, 1999). In absolute, the impact of infrastructures on regional development is controversial, and this is true also for the infrastructural investments made within Cohesion Policy, as discussed in Section 2. In particular, transport and ICT/digital infrastructural investments can be detrimental in disadvantaged contexts where the other growth determinants remain weak (Elburz et al., 2017). As far as transport infrastructures are concerned, the New Economic Geography literature has shown how decreasing transportation costs moderates costs of trade, pushing firms to cluster together to benefit from economies of scale, thus generating a core-periphery structure (Krugman & Venables, 1990); moreover, decreasing costs of transportation can end up favoring more the already developed economies by allowing their firms to penetrate the market of peripheral markets from afar. In the case of ICT/digital infrastructures, the impact is overall positive (Elburz et al., 2017; Greenstein & McDevitt, 2009; Grimes et al., 2012; Madden & Savage, 1998; Vu, 2011), but there might be disparities in benefitting from the public policy that favors above-average skilled workers, higher income population and IT-intensive firms (Akerman et al., 2015; Forman et al., 2012; Kolko, 2012). It is in this perspective that Rietveld and Bruinsma (2012) discuss the role of the factors influencing the infrastructure supply and that by focusing on ICT investments, Tranos (2012) concludes that they are necessary but not sufficient: abilities and specific know-how to exploit the new technology are needed, and therefore, he argues, public policy should jointly focus on these capabilities to foster growth.[2]

In the case of *Soft* investments (broadly intangibles: firms' support, R&D, measures to improve institutional quality and public administration efficiency), the return is broadly recognized to be averagely

[2]Tranos (2012), echoing Cohen and Levinthal (1990), calls this ability "absorptive capacity."

positive, although indirect effects have been discussed both from a theoretical (Kline & Moretti, 2014) and an empirical point of view with special reference to firms' incentives (Accetturo & de Blasio, 2019; De Blasio et al., 2015). Section 2 reviewed the papers on intangible investments within the Cohesion Policy framework.[3]

Due to the complementarities between the different growth determinants that the two categories of investment address, the aggregated return associated with the joint implementation of the two types of investments can be greater than the sum of the returns of the single headings.

Based on the above evidence, *Hard* investments must be accompanied by *Soft* investments for different reasons. In order for regions to be ready to get their accessibility improved without suffering from the displacement of economic assets/activities and consequences of the increased competition, the local socioeconomic environment needs to be solid. *Soft* investments are key in this respect, improving the quality of the business environment, innovation system, and building administrative capacity. Regarding the return of digital infrastructure, *Soft* investments are necessary to ensure that regional skills are adequate and capable of dynamically dealing with the management and use of continuously renovated platforms. More generally, *Soft* investments in institutional quality and public administration efficiency contribute to the timely and qualitative implementation of the policy in all contexts (Milio, 2007).

Conversely, the intangible assets supported by *Soft* investments might also benefit from the provision of Hard investments. Improving the infrastructural endowment of a particular area helps build up the system of proximities that allows more accessible connections, favoring spatial spillovers, adoption of innovation, and knowledge flows/externalities (Capello, 2015; Capello & Nijkamp, 1996; Capello, 2015; Del Bo & Florio, 2012). These assets are key to enable the effectiveness of policies promoting endogenous local economic development (Crescenzi & Giua, 2016). In addition, the proximities provided by increasing connections contribute to the generation of wider (spatial or relational) scales at which advanced projects promoted by *Soft* investments need to be developed (e.g., for managing global challenges in the energy and green transition).

4 | DATA AND DESCRIPTIVE STATISTICS

To investigate how the aggregated impact of Cohesion Policy depends on the composition of the regional expenditure, we rely on the European Commission-DG REGIO data on Cohesion Policy investments by priority, year, and NUTS2.[4] To maximize coherence within the priorities; we focus on one programming period only (2007–2013). We aggregated the different EU priorities into two macro-categories. *Hard* investments include transport, IT, energy, and social infrastructure; *Soft* investments include business support, R&D, human resources, and capacity-building measures.[5]

The outcome variable is the average GDP growth rate from 2007 to 2016.[6] Outcome variable and covariates are retrieved from Cambridge Econometrics and Eurostat.

Table 1 shows descriptive statistics for treatment and outcome variables.[7] Most of the EU regions spent less than 700 euros per capita. On average, regions allocate more than 45% of the total funds to *Soft* investments, whereas *Hard* investments account for roughly 30%. The rest of the expenditure is employed in

[3]The literature focusing on the impact of policies supporting one or more of these drivers is enormous and its review is beyond the scope of this article.
[4]Data reports commitments/expenditure disaggregated into the EU priorities at the NUTS2 level for the 2000-2006 and 2007-2013 programming period. Data covers European Regional Development Fund and Cohesion Fund. Unfortunately, European Social Fund data are not available. This limitation has been faced by previous work already (Ciffolilli et al., 2015; Percoco, 2013).
[5]Sample size restrictions impede testing the impact of more complex and realistic financing mixes by increasing the number of treatment dimensions.
[6]For robustness and accounting for the medium-run effect, we run the analysis considering also the more extended period between 2007 and 2019. Results are similar and are available upon request.
[7]We correct both treatment and outcome variable for inflation (ref.: year 2015) and differences in purchasing power parities. Multipliers have been retrieved from Eurostat.

TABLE 1 Descriptive statistics.

	Mean	SD	Min.	Max.
Total funds p.c.	580.75	1072.54	1.431	6624.90
Hard investments p.c.	263.68	592.87	0.003	4934.57
Soft investments p.c.	161.20	257.54	0.913	1616.49
Hard investments (share)	0.299	0.187	0.000	0.751
Soft investments (share)	0.458	0.222	0.049	0.953
GDP p.c. growth rate 2007–2016	0.015	0.017	−0.032	0.065
Observations	238			

Note: All variables are corrected for inflation and purchasing power parity differences.
Source: authors' own elaborations on data DGCEE.

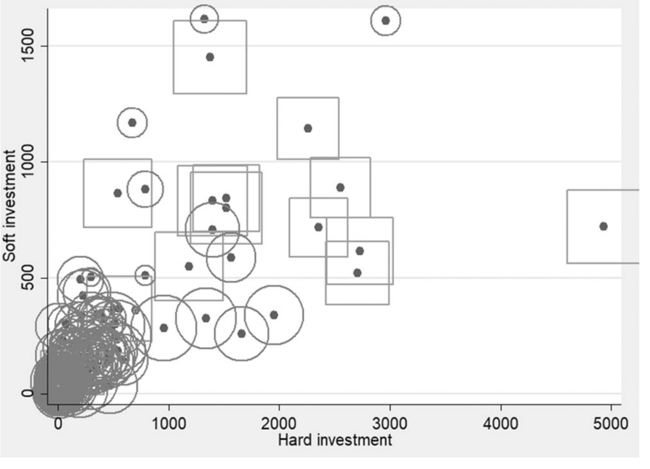

FIGURE 1 Investment mix and GDP average growth rate in the period 2007–2016. Circles represent a positive growth rate. Squares represent a negative growth rate. The diameter is proportional to the region's GDP growth rate. *Source*: Authors' own elaborations on data DGCEE.

a residual category, including priorities classified as Tourism and Culture, Urban and rural regeneration, Environment and natural resources. The average growth rate of the GDP pc over 2007–2016 is very low (0.015).

Figure 1 presents a scatterplot in which the two axes are given by hard (horizontal axis) and soft investment per region (vertical axis); each dot represents a region. The size of the bubbles (circles/squares) accounts for the region's per-capita GDP growth rate (positive/negative). We can see that no clear pattern emerges for the size of the bubble, that is, it is not clear if an increase in one or both kinds of funds leads to higher GDP growth. Indeed, the size of the bubbles is similar for regions close to the origin of the axes and those far away from there. This difficulty in singling out potential patterns of the GDP growth in relationship to funds' "intensity" and "mix" —that is, different sets of percentages of Hard and Soft investment—is at the heart of the counterfactual strategy that we are proposing here to identify the impacts of the different "mix" of funds.

5 | METHODOLOGY

The methodology employed in the paper extends the generalized propensity score (Hirano & Imbens, 2004) to multiple continuous dimensions, as proposed by Egger and von Ehrlich (2013). Such an estimator allows not only to estimate the correlation between a treatment and an outcome variable but also to establish a precise causal nexus between the variables. Overall, the identification strategy is based on the assumption of selection based on observables. Once we condition on the propensity score, the potential outcome is independent of the treatment so that we can safely estimate the dose-response function. The procedure is similar to the generalized propensity score for continuous treatment (Becker et al., 2012; Hirano & Imbens, 2004)—see Appendix A for more technical details. In particular, we consider a bi-dimensional continuous treatment.

At first, each dimension of the treatment (*Hard* and *Soft* investments) is regressed on a series of covariates (cf. Tables B1 and B2 in the Appendix for descriptive statistics and regression results) for estimating the propensity score and ensuring comparability within the sample of regions associated with different treatments. By following the literature, covariates include the average per capita GDP in the 5 years before the programming period and other proxies of the economic structure of the region: to account for the industrial structure, we control for the shares of employed in the agriculture industry (no construction) and financial and business services. As far as the labor market is concerned, we consider the employment rate and the total employment in the region. The overall presence of factors is then proxied by the gross fixed capital formation and compensation of employees (i.e., the total remuneration received by employees comprising wages and salaries and employers' social contributions). Finally, we add to the covariates the per capita amount of Cohesion Policy funds allocated for priorities that are not included in the *Hard* nor the *Soft* investments groups.

To guarantee the comparability between regions and satisfy the balancing property, we restrict our analysis to the regions lying on the common support. The common support sample includes regions with a higher per capita GDP, lower occupation in Agriculture, and higher occupation in the service sector. While the total employment is similar for the two groups, the employment rate tends to be higher for the regions on the common support. Regions on common support and outside common support also differ for the Gross domestic expenditure on R&D as a percentage of GDP and for the kilometers of motorways per thousand square kilometers. In particular, the difference in mean between regions on the common support and outside common support is 130.6 euros (p-value t-test <0.05) of Gross domestic expenditure on R&D percentage of GDP and 19.2 km of motorways per thousand square kilometers (p-value t-test <0.05). Although these statistics are flawed by a significant number of missing values (when considering only observations with nonmissing values in both variables, the sample reduces from 238 to 160 observations), they suggest that the infrastructural endowment of regions on the common support is significantly higher than those outside the common support. Moreover, the regions inside the common support also spend more on R&D.

EU regions included in the common support are 112. They account for 14% of the total allocation in the sample (roughly 25 of the 182 billion inflation-corrected PPP allocated). These regions correspond to the regions Becker et al. (2012) call "low transfer intensity." Due to the composition of the common support group (the group of regions that are included in our analysis), our findings will be informative for the EU's More Developed regions only. In contrast, the present study results cannot be extended to Less Developed regions.

We use the estimated propensity score to generate four groups of regions (based on the intensity of treatment received), and we test the balancing properties among them. Since with a continuous dimension, the distinction between control and treated groups is not possible; we divide the sample into subsets based on the range of the treatment and then, in turn, consider one subset as the treated group and the others as the control group. Then we test whether covariates differ after adjusting for the propensity score. The procedure is the multidimensional analog to the t-test that is commonly implemented in the cases of binary treatment to test the similarity in means before and after the matching (Leuven & Sianesi, 2003). Table B3 in the Appendix shows the mean differences between groups for each covariate before and after adjusting for the propensity score.[8] Considering a significance level of 5%, we obtain a satisfying bias reduction by controlling for the propensity score: the significant tests are reduced from 18 (prematching) to 4 (postmatching).

The last step for adequately identifying the dose-response function consists of estimating a flexible control function regressing the outcome on treatment dimensions and propensity score. The resulting coefficients will be used for estimating the dose-response function. In particular, we estimate a polynomial with the treatment, the propensity score, and interactions up to degree two.[9] For the sake of brevity, we report the details of the estimation in Appendix C.

6 | RESULTS

The results of the estimation of the dose-response function are shown in Figure 2.[10] The overall effect of the Cohesion Policy in our sample is positive and equal to an average increase of 0.8% in terms of GDP p.c. growth rate over the period. The result aligns with the existing literature, see Becker et al. (2012), even if our analysis focuses on a limited subsample of regions to guarantee comparability between the observations.

Figure 2 also shows the impacts achieved by the different expenditure mixes confirming how the mix between *Hard* and *Soft* investments is crucial in determining growth.

If the expenditure is polarized toward one of the two fields, positive impacts generate only when this field is the *Soft* investments one. When only a limited part of the budget is allocated to *Soft* investments, also *Hard* investments deliver negligible (or even detrimental) impact. In the presence of consistent *Soft* investments, *Hard* investments also become impactful. When both types of investment have a high magnitude, the positive effects of both kinds of investments magnify, activating the synergies discussed in Section 3.

These results may partly be driven by the fact that the regions included in our common support already benefit from a certain infrastructural endowment. The present analysis cannot exclude that different types of regions (e.g., less developed regions lacking infrastructures) would benefit more, irrespective of the intensity, from investments in infrastructure. The large infrastructural endowments of common support regions could also explain why the gains obtained coupling high-intensity *Hard* and *Soft* investments are comparable to those obtained with high-intensity *Soft* investments alone. When a region is already provided with a sufficient level of *Hard* investments, due to the diminishing return of the infrastructural investment, the bulk of the gains depends on using those infrastructures efficiently and developing an ecosystem capable of extracting value from the existing asset rather than constructing new assets per sé.

The above results confirm the presence of nonlinear effects of the funds intensity on GDP growth (Becker et al., 2012; Cerqua & Pellegrini, 2018). Nonetheless, it enriches the interpretative framework in two directions. First, it suggests possible nonlinearities in more than one "intensity." Second, it suggests the existence of nonlinearities also in the "policy mix" that we investigate further in the remainder of this Section.[11]

Based on the results provided by the estimation of the dose-response function, Table 2 shows how, on average, under the constraint of the available resources, different mixes of *Hard* and *Soft* investments could have doubled the average per capita growth rate during the 2007–2016 period (from 0.8% to 1.7%).

[8]We also tested whether the past GDP growth of regions—up to two-time lags—is balanced in the groups to neutralize potential heterogeneous effects of business crisis during the time window under analysis.

[9]As a robustness check, we run the same analysis with a polynomial of order three obtaining consistent results (tables are not reported for the sake of brevity).

[10]The figure is built as follows. For each dimension, we selected 100 equidistant points within its range. The Cartesian product then defines the set of treatments for which we estimate the dose. Bias corrected method (BC) confidence intervals (Carpenter & Bithell, 2000; Efron & Tibshirani, 1994) are then computed for each estimated response using 1000 bootstrap samples.

[11]Results of the different studies are computed by applying different methods and focuses. Thus, special care should be used to compare them.

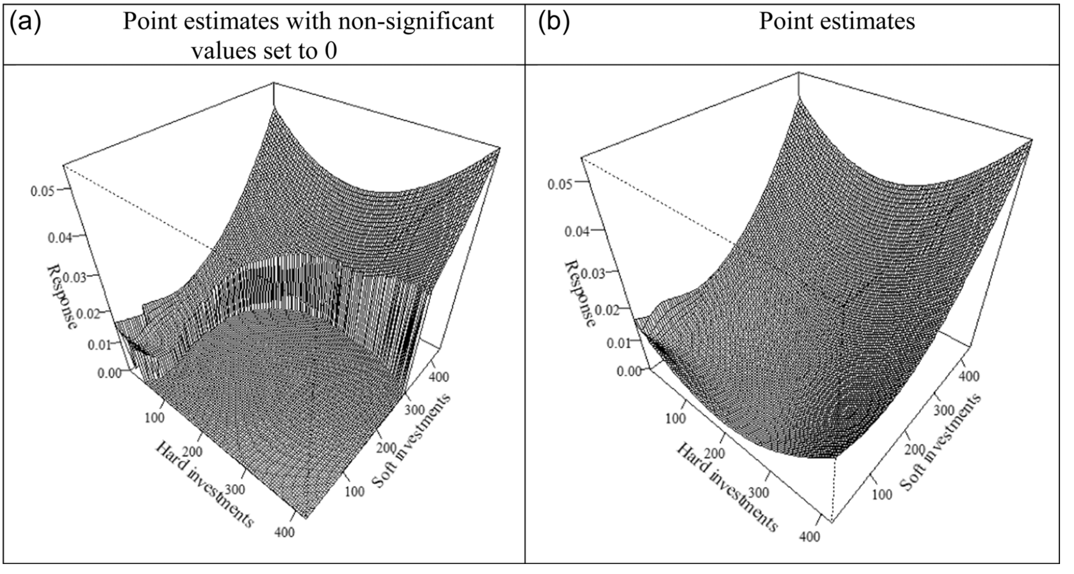

FIGURE 2 Dose response function. (a) Point estimates with nonsignificant values set to 0. (b) Point estimates. *Source*: Authors' own elaborations on data DGCEE.

TABLE 2 Policy mix and GDP growth rate: observed and counterfactual values.

Variables	Mean	SD	Min.	Max.
Observed *Hard* investments p.c.	34.11	71.03	0.014	418.7
Observed *Soft* investments p.c.	68.82	73.43	4.816	437.7
Counterfactual *Hard* investments p.c.	11.83	47.07	0.014	305.7
Counterfactual *Soft* investments p.c.	88.19	98.68	4.816	437.7
Observed *Hard* investments (share)	0.259	0.172	0.0002	0.874
Observed *Soft* investments (share)	0.741	0.172	0.126	1.000
Counterfactual *Hard* investments (share)	0.0379	0.069	3.90e−05	0.411
Counterfactual *Soft* investments (share)	0.962	0.069	0.589	1.000
Observed GDP p.c. growth rate	0.0084	0.006	0	0.038
Counterfactual GDP p.c. growth rate	0.0169	0.0058	0.014	0.043
Difference Growth rate	0.0086	0.0080	0	0.043
Observations (common support)	112			

Note: All variables are corrected for inflation and purchasing power parity differences.
Source: Authors' own elaborations on data DGCEE.

Under the constraint of the available resources, the impact in terms of GDP growth rate could have been raised from 0.8% to 1.7% by pursuing a policy mix where, on average, *Hard* investments decrease (−22.28 euro per capita) in favor of *Soft* investment (+19.37 euro per capita). In terms of shares, this would correspond to a recomposition of the policy mix from an average of 26% (*Hard*)—74% (*Soft*) to an average of

4% (*Hard*)—96% (*Soft*).[12] The exercise suggests that regions tend to spend in *Hard* investments more than the quantity necessary to optimally foster growth. More in general, it confirms the role of the policy mix as a key conditioning factor for the overall impact achieved by the Cohesion Policy.

Finally, we integrate our analysis by investigating if and to what extent a comparable role is played, also by the amount of available resources. With this aim, we generate two scenarios where for each region, we increase the available funds by 50% and by 100%. We found that (i) an increase of available funds equal to 50% would have led to a GDP p.c. average growth rate comparable to the one obtained with the funds spent; (ii) an increase of available funds equal to 100% would determine an average GDP growth rate of around 2% (vs. 0.8%). This means that the impact on the GDP growth rate associated to a doubled amount of available funds (2%) is perfectly comparable to the impact on the GDP growth rate that would be obtained by simply changing the policy mix, as depicted in Table 2 (1.7%). This final exercise suggests that, at least for More Developed regions, the improvement of the policy mix represents a more viable way than the increase of available resources.

This last result shows why the analysis conducted in the present paper is crucial. Indeed, it suggests that policymakers do not need to find and provide regions additional funds to spur growth but that it can be sufficient to reallocate them into different categories of expenses following the criterium of the "policy mix" introduced above.

7 | CONCLUSIONS

This paper focused on the conditioning effect that the composition of the expenditure in different fields of intervention can play on the aggregated impact of the policy. The study aims to increase the policy relevance of the findings provided by the literature on Cohesion Policy impact by advising the regional responsible for the Policy on how to allocate the available resources across different fields of intervention to obtain a greater impact (Berkowitz et al., 2020).

We identified Cohesion Policy as a multidimensional treatment composed of *Hard* (infrastructures) and *Soft* (business and technical support) investments. By applying a generalized propensity score analysis in a multiple continuous treatment scenario, we estimated how the Cohesion Policy impact in terms of regional economic growth depends on how the investments of the two fields are mixed.

We found that when the expenditure is polarized toward one of the two fields, positive impacts generate only when this field is the *Soft* investments. When only a limited part of the budget is allocated to *Soft* investments, also *Hard* investments deliver negligible (or even detrimental) impact. In the presence of consistent *Soft* investments, *Hard* investments also become impactful.

Under the constraint of the available resources, the impact in terms of GDP growth rate could have been raised from 0.8% to 1.7% by pursuing a policy mix where, on average, *Hard* investments decrease (−22.28 euro per capita) in favor of *Soft* investment (+19.37 euro per capita). In terms of shares, this would correspond to a recomposition of the policy mix from an average of 26% (*Hard*)—74% (*Soft*) to an average of 4% (*Hard*)—96% (*Soft*).

The improvement such a recomposition would deliver is comparable to the one obtained by at least doubling the available resources. The cohesion Policy could have led to better results if available resources would have been allocated differently. Working on the policy mix is more important than increasing expenditure.

It is worth recalling once again that the characteristics of the regions included in the common support of our analysis are typical of the More Developed Regions of the EU. Hence our findings are not extendable to Less Developed Regions.

The paper's contribution is to extend the set of empirical results on Cohesion Policy impacts with original evidence on the conditioning role that the composition of the expenditure in different fields of intervention can

[12] In this case, funds spent in residual categories are not considered (we control for this aspect by including a covariate in the identification of the common support).

play on the aggregated causal impact of the policy. Our findings also have relevance in the current context of Next Generation EU. Digital and green transitions should involve a mix of interventions where investments in infrastructures must be the protagonist in terms of resources and accompanied by investments in business and technical support capable of reinforcing intangible assets. Infrastructural modernization (e.g., broadband networks and renewable energy systems) can drive the success of the recovery and resilience processes pursued within the NGEU framework but it has to be radical and linked with programs supporting adequate skills and technical support for citizens, firms, and local administrations (e.g., digital education; blockchain platforms, e-government). Alternatively, resources are better employed in *Soft* investments, the impact of which is not conditioned by the magnitude of the investment or by necessary synergies.

Due to the methodological characteristics of the model, which is run on a common support of observations mostly including more advanced regions, our results cannot be generalized to the sub-sample of less developed regions. Indeed, working on a methodological approach able to provide a more general version of the results obtained so far is on our future agenda.

A second limitation concerns the limited number of treatment dimensions considered: it would certainly be interesting to disentangle the policy intervention in more than two broad categories. This would support an easier transformation of the evidence provided in actionable policy decisions within the Cohesion Policy and/or other policies' domains. Further research avenues should be processed in these directions. In particular, they will require improving data (on the policy expenditure and on outcomes/covariates) and methods (within the counterfactual domain) to increase the analysis level of detail. This would be a key improvement with the aim of enabling more precise policy recommendations.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Enrico Cristofoletti http://orcid.org/0000-0003-2373-2522
Roberto Gabriele http://orcid.org/0000-0003-4819-0758

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APPENDIX A

The methodology employed in the paper consists of the extension to multiple continuous dimensions of the generalized propensity score (Hirano & Imbens, 2004) proposed by Egger and von Ehrlich (2013).

Given a sample of N units, $T_i = (T_{1i}, \ldots, T_{Mi})'$ is the random variable concerning the treatment-experienced the ith unit. M is the number of dimensions of the treatment. In our case $M = 2$, namely *Hard* and Soft investments.

The level of the treatment is defined by an m-equation structural model where the reduced equations are defined as:

$$T_{mi} = f(Z_i, \gamma_m) + v_{mi}, m = 1, \ldots, M, \tag{A1}$$

$Z_i = \bigcup_m^M X_{mi}$ is the union of the exogenous variables X_{mi} and possibly their interaction terms.

We are interested in the average dose response function:

$$\mu(t) \equiv E[Y_i(t)],$$

where $Y_i(t)$ is the potential outcome for the ith unit when treated with $t \in \mathfrak{I}$. $\mathfrak{I}$ is the set of all possible treatments. For the dose-response function to be identifiable weak unconfoundedness must hold:

$$Y_i(t) \perp T_i | Z_i \; \forall \; t \in \mathfrak{I}.$$

It means that once conditioned on Z_i, the potential outcome and the experienced treatment are independent.

The conditional density function of the treatment given the covariates, is defined as:

$$g(t, z) \equiv f_{T_i|Z_i}(T_i = t | Z_i = z).$$

The generalized propensity score is instead defined as the random variable:

$$G_i = g(T_i, Z_i).$$

The propensity score generates a family of random variables (t, Z_i), $\forall \; t \in \mathfrak{I}$.

We assume that $T_i|Z_i \sim \mathcal{N}(\mathbf{f}(\mathbf{Z_i}, \boldsymbol{\gamma_m}), \Sigma)$, $\quad m = 1, \ldots, M$, that is: the conditional distribution of the treatment given the covariates is a multivariate normal distribution with constant between observations variancee–covariance matrix. This implies that $\mathbf{v_i} = (v_{1i}, \ldots, v_{Mi}) \sim \mathcal{N}(\mathbf{0_m}, \Sigma)$ and that the variance covariance matrix Σ is equal $\mathrm{Cov}(v_1, \ldots, v_M)$ where $v_m = (v_{1m}, \ldots, v_{Nm})$.

The generalized propensity score for the ith unit is then:

$$G_i = \frac{1}{(2\pi)^{\frac{M}{2}} \det(\Sigma)^{\frac{1}{2}}} \exp\left\{-\frac{1}{2} \mathbf{v}_i' \Sigma^{-1} \mathbf{v}_i\right\}.$$

While the estimated one is:

$$\hat{G}_i = \frac{1}{(2\pi)^{\frac{M}{2}} \det(\hat{\Sigma})^{\frac{1}{2}}} \exp\left\{-\frac{1}{2} \hat{\mathbf{v}}_i' \hat{\Sigma}^{-1} \hat{\mathbf{v}}_i\right\}.$$

The estimated quantities are obtained by estimating (A1) by OLS.

The propensity score satisfies by construction the balancing property:

$$Z_i \perp 1\{T_i = t\} | g(t, Z_i) \; \forall \; t \in \mathfrak{I}.$$

It can be shown (Egger & von Ehrlich, 2013) that weak unconfoundedness and balancing property imply:

$$Y_i(t) \perp T_i | g(t, Z_i), \forall \; t \in \mathfrak{I}.$$

That is, the potential outcome is independent from the treatment once we have conditioned on the propensity score calculated at t.

Therefore

$$E[Y_i | T_i = t, g(T_i, Z_i)] = E[Y_i(t) | T_i = t, g(t, Z_i)] = E[Y_i(t) | g(t, Z_i)],$$

and

$$\mu(t) \equiv E[Y_i(t)] = E_g[E[Y_i(t) | g(t, Z_i)]].$$

This means that we can retrieve the dose-response function for t by estimating $E[Y_i | T_i, g(T_i, Z_i)]$ with a flexible polynomial of T_i and $g(T_i, Z_i)$. Then, we can use the resulting coefficients to predict $E[Y_i(t) | g(t, Z_i)]$ for each i. Finally, by taking the average of the predictions, we recover $\widehat{E[Y_i(t)]}$.

We now summarize how to identify the common support and to test the balancing property.

According to Flores et al. (2012) and Egger's generalization to a multidimensional treatment (Egger et al., 2020) the common support can be obtained by partitioning the treatment in an arbitrary number of subsets, S, indexed by D. Then for each discrete subset T^D we chose a representative point $\overline{t_D}$. There, we calculate the propensity score, $G_i(t_D) = g(t_D, Z_i)$, for each observation in the sample.

We then keep all the observations such that:

$$G_i(\overline{t_D}) \in \left[\max\left\{\min_{j \in T^D}(G_j(\overline{t_D})), \min_{j \notin T^D}(G_j(\overline{t_D}))\right\}, \min\left\{\max_{j \in T^D}(G_j(\overline{t_D})), \max_{j \notin T^D}(G_j(\overline{t_D}))\right\}\right]; for\ D = 1, \ldots, S.$$

The balancing property is tested using a procedure that mimics the one in Bia and Mattei (2008) for the one-dimensional continuous case. The treatment is partitioned into an arbitrary number of subsets. Then, for each subset, we do the following. A representative point is chosen, and the propensity score at that point is calculated for each unit. The calculated propensity scores are also partitioned in an arbitrary number of subsets. For each exogenous variable, the weighted average of the differences in the mean between the focal subset of the treatment and the others within the same subset of the propensity score is computed. This generates the following test statistics:

$$\frac{1}{N} \sum_{g(\bar{t}, Z)^D} N_{g(\bar{t}, Z)^D} (\overline{Z}_{T^D g(\bar{t}, Z)^D} - \overline{Z}_{T^{-D} g(\bar{t}, Z)^D}),$$

where N is the number of observational units in the sample, and $N_{g(\overline{t}, Z)^D}$ is the number of observations in a given interval of the propensity score $g(\overline{t}, Z)^D$. $\overline{Z}_{T^D g(\overline{t}, Z)^D}$ is the sample mean of the exogenous variable for those observations that belong to intersection between the subset of the treatment T^D and interval of the propensity score $g(\overline{t}, Z)^D$. $\overline{Z}_{T^{-D} g(\overline{t}, Z)^D}$ is instead the sample mean of the exogenous variable for those observations that belong to the intersection between the subset of the treatment T^D and interval of the propensity score $g(\overline{t}, Z)^D$. A t-test evaluates if the test statistics is different from 0.

APPENDIX B

TABLE B1 Variables used for the estimation of the propensity score—descriptive statistics.

	Time coverage	Mean	SD	Max.	Min.
Per capita GDP	2002–2006	19594.427	11416.412	53066.062	30.080
Total employment		801814.839	712651.275	5.887e+06	25638.800
Employment rate	2006	63.956	7.441	79.200	41.700
Gross fixed capital formation	2002–2006	8.130e+09	1.053e+10	9.615e+10	8.805e+06
Compensation of employee	2002–2006	1.779e+10	2.392e+10	2.446e+11	1.504e+07
Residual categories funds	2002–2006	155.875	294.313	2055.546	0.007
Share of employed in agriculture	2002–2006	0.074	0.090	0.542	0.000
Share of employed in industry (excluding construction)	2002–2006	0.182	0.073	0.376	0.029
Observations		238			

Note: All monetary variables are corrected for inflation and purchasing power parity differences. Residual categories Funds are expressed in per capita term.

Source: Authors' own elaborations on data DGCEE.

TABLE B2 GPSM first stage estimation—hard and soft investments.

Variables	(1) *Hard* investments	(2) *Soft* investments
Per capita GDP	0.0006***	0.0006***
	(0.0001)	(0.0000)
Per capita GDP · share services	−0.0014**	−0.0011***
	(0.0007)	(0.0004)
(Per capita GDP)^2	−2.33e−08***	−1.94e−08***
	(5.71e−09)	(3.35e−09)
(Per capita GDP · Share agriculture)^2	−1.46e−07	−1.13e−07
	(1.40e−07)	(8.22e−08)
(Per capita GDP · Share industry)^2	−1.11e−07**	−6.61e−08**
	(4.92e−08)	(2.89e−08)
(Per capita GDP · Share Services)^2	2.11e−07**	1.39e−07**
	(1.03e−07)	(6.08e−08)
(Per capita GDP)^3	3.22986e−13***	2.30091e−13***
	(8.18560e−14)	(4.80969e−14)
(Per capita GDP · Share agriculture)^3	2.81780e−11	1.66460e−11
	(2.70626e−11)	(1.59015e−11)

TABLE B2 (Continued)

Variables	(1) *Hard* investments	(2) *Soft* investments
(Per capita GDP · Share industry)^3	5.44817e−12	3.76096e−12
	(4.88679e−12)	(2.87138e−12)
(Per capita GDP · Share services)^3	−1.33090e−11***	−7.34561e−12**
	(5.07035e−12)	(2.97923e−12)
Share of employed in agriculture	4.2200**	2.7900***
	(1.7200)	(1.0100)
Total employment	8.09e−07*	7.20e−07***
	(4.58e−07)	(2.69e−07)
Employment rate	−0.0947***	−0.0252***
	(0.0165)	(0.0096944)
Gross fixed capital formation	4.44705e−11	−3.38150e−11
	(4.33402e−11)	(2.54658e−11)
Compensation of employee	−4.14641e−11**	−8.55092e−12
	(1.84026e−11)	(1.08130e−11)
Residual categories funds	0.0025***	0.0015***
	(0.0005)	(0.0003)
Share of employed in industry (excluding construction)	9.0900***	3.9000**
	(2.8200)	(1.6600)
Constant	5.2300***	2.2700***
	(1.4400)	(0.8490)
Observations	238	238
R^2	0.6790	0.6750
Adj. R^2	0.6540	0.6500

Note: Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Source: Authors' own elaborations on data DGCEE.

TABLE B3 Balancing test for covariates pre- and postmatching.

Groups	Not adjusted (prematching) 1	2	3	4	Adjusted (postmatching) 1	2	3	4
Per capita GDP	0.029*	0.694	0.838	0.013*	0.686	0.869	0.865	0.317
Per capita GDP · Share services	0.002*	0.150	0.244	0.096	0.055	0.351	0.250	0.515
(Per capita GDP)^2	0.045*	0.621	0.790	0.042*	0.611	0.999	1.000	0.372
(Per capita GDP · Share agriculture)^2	0.008*	0.048*	0.118	0.949	0.004*	0.209	0.535	0.417
(Per capita GDP · Share industry)^2	0.029*	0.888	0.096	0.065	0.304	0.605	0.188	0.322
(Per capita GDP · Share services)^2	0.015*	0.255	0.319	0.215	0.119	0.422	0.346	0.521
(Per capita GDP)^3	0.066	0.555	0.743	0.104	0.524	0.851	0.878	0.430
(Per capita GDP · Share agriculture)^3	0.004*	0.028*	0.186	0.734	0.001*	0.132	0.632	0.674
(Per capita GDP · Share industry)^3	0.029*	0.931	0.090	0.077	0.266	0.602	0.179	0.312
(Per capita GDP · Share services)^3	0.057	0.344	0.441	0.359	0.200	0.459	0.479	0.568
Share of employed in agriculture	0.034*	0.208	0.099	0.918	0.117	0.676	0.501	0.201
Total employment	0.044*	0.369	0.157	0.559	0.056	0.475	0.114	0.358
Employment rate	0.189	0.775	0.509	0.098	0.94	0.98	0.663	0.288
Gross fixed capital formation	0.025*	0.184	0.246	0.548	0.056	0.269	0.187	0.621
Compensation of employee	0.042*	0.497	0.142	0.409	0.088	0.691	0.116	0.488
Residual categories Funds	0.000*	0.656	0.770	0.000*	0.000*	0.806	0.798	0.000*
Per capita GDP	0.287	0.727	0.104	0.580	0.408	0.814	0.114	0.711

Note: $^*p < 0.05$.
Source: Authors' own elaborations on data DGCEE.

APPENDIX C

In Table C1, we report the results for the estimation of the flexible control function. We estimate a polynomial with the treatment, the propensity score, and interactions up to degree two.[13] According to Hirano and Imbens (2004), the model does not have a causal interpretation (it is an intermediate step for estimating the dose-response function); the only valuable information is whether the GPS terms are significant. If it is the case, the observable covariates matter for selection into treatment intensities. We conclude that it is the case since we observe GPS interaction terms with *Soft* investments significant at the 10% level.

[13] As a robustness check, we run the same analysis with a polynomial of power three obtaining consistent results (tables are not reported for the sake of brevity).

TABLE C1 Regression with a flexible polynomial.

Variables	(1) GDP p.c. growth rate
Hard investments	−0.0001**
	(6.40e−05)
Soft investments	−6.79e−05
	(5.27e−05)
Generalized propensity score (GPS)	−1.5200
	(4.0200)
Hard investments · GPS	−2.3700
	(2.0800)
Soft investments · GPS	0.4700*
	(0.2570)
$(\text{Hard investments})^2$	3.56e−07**
	(1.66e−07)
$(\text{Soft investments})^2$	3.21e−07**
	(1.29e−07)
$(\text{GPS})^2$	549.0000
	(412.0000)
$(\text{Hard investments} \cdot \text{GPS})^2$	145.0000
	(290.0000)
$(\text{Soft investments} \cdot \text{GPS})^2$	−5.3200*
	(2.8600)
Constant	0.0167***
	(0.0047)
Observations	112
R^2	0.2780

Note: Standard errors are in parentheses. Dependent variable: average GDP growth rate. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Source: Authors' own elaborations on data DGCEE.