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Cross-Regional Sequential Difference in Difference (CR-SEQDD):

An Empirical Approach for Evaluating EU Thematic-Objective Interventions with Regional Data Aggregated at the National Level

Technical Note

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ABSTRACT

Causal impact evaluations of EU Operational-Programme (OP) interventions aggregated at the national level are often used as a tool to inform policy makers, and the public opinion in general, about the overall contribution of the European Funds in achieving desirable results within the various thematic objective (TO) areas. Implementing these types of TO evaluations, however, is a very challenging task because, in the case of data aggregated at the national level, very often, no comparable "untreated" units of observation can be found for the analysis, due to the unique features of the EU member states and small sample sizes. For these reasons, standard quasi-experimental empirical methods can be very rarely implemented and identifying casual effects of the OP interventions without very strict and limiting casual-identification assumptions is merely impossible. Indeed, it should be understood that, in general terms, there is a clear trade-off between rigorous internal validity of casual-effect evaluations and the level of aggregation of OP interventions and result indicators: the more the analysis is focused on broad TOs at the national level, the more limited the internal validity tend to be; the more the focus is on specific interventions at a micro-level, the stronger the internal validity tend to be. This technical note discusses an empirical approach, called "Cross-Regional Sequential Difference-in-Difference" (CR-SEQDD) that exploits the regional variations in the intensities of the OP interventions, pertaining to a same TO, in order to estimate a dose response functions that, under very strict and limiting causal-identification assumptions, can be subsequently used to establish what part of a change in the nationally-recorded result indicator (Y) of interest is likely to be caused by the OP interventions and what part is instead due to a counterfactual spontaneous change. This is done by means of pairwise sequential difference-in-difference (DD) comparisons across regions with different intensities of the OP interventions. These DD estimations are then plotted against the related cross-regional differences in the intensities of the OP interventions and a fitting dose-response function is estimated to subsequently infer about the casual effect of the nationally-aggregated set of OP interventions considered in the analysis. Under sufficient data-availability scenarios, compared to different evaluation options, such as expert opinions or meta-analyses, the CR-SEQDD estimation procedure has the advantage of allowing a more consistent comparisons of the findings across different thematic areas, programming periods and EU countries.

1 INTRODUCTION

The aim of impact evaluations commissioned on programme interventions funded by the European Structural and Investment Funds (ESIF) is at times to assess the causal effects produced at the national level on result indicators pertaining to thematic objectives (TOs)[1] identified in the partnership agreements (PAs)[2]. These thematic evaluations of the PA imply a very high level of aggregation: all operational programmes (OPs) interventions are pooled together by thematic objective at the national level. These types of evaluations are often a tool to inform policy makers, and the public opinion in general, about the overall contribution of the European funds in achieving, at the national level, desirable results within the various thematic objective areas. The findings from these types of evaluations are useful at a very high decision level that pertains the choice, at the macro level, of where to allocate resources among largely-defined domains of program interventions.

For each result indicator Y (also referred to as outcome variable[3]) identified with reference to a specific TO, the main challenge for the analysis is to separate the part of the before-after-intervention change of Y that was caused by the ESIF support from the part of the change that was caused by other factors (unrelated to the ESIF interventions). This is a very important aspect because it prevents the reported findings, conclusions and recommendations being based on naïve result-indicator analyses that offer evidence under the assumption of a-priori flat spontaneous-change trend of Y (and that, for this reason, are potentially full of "spontaneous-change" bias, Figure 1). For these types of thematic objective evaluations of ESIF support, however, estimating "causal impacts"[4] is a very challenging task and every possible option has many limitations and a low-level of rigorous internal validity.

[1] Thematic objectives are in terms of 11 investment priorities for the implementation of ESIF support: 1. Strengthening RTDI; 2. Enhancing access to, and use and quality of information and communication technologies (ICT); 3. Enhancing the competitiveness of SMEs; 4. Supporting the shift towards a low-carbon economy; 5. Promoting climate change adaptation, risk prevention and management; 6. Preserving and protecting the environment and promoting resource efficiency; 7. Promoting sustainable transport and removing bottlenecks in key network infrastructures; 8. Promoting sustainable and quality employment and supporting labour mobility; 9. Promoting social inclusion, combating poverty and any discrimination; 10. Investing in education, training and vocational training for skills and lifelong learning; 11. Enhancing institutional capacity of public authorities and stakeholders and efficient public administration.

[2] Partnership Agreements define the strategy and investment priorities chosen by the Member State and present a list of national and regional operational programmes (OPs), as well as an indicative annual financial allocation for each OP.

[3] In the scientific empirical impact evaluation literature, "result indicators" can also be referred to as "outcome variables", "result variables" or "outcome indicators" (all these terms can be used uniquely and consistently throughout a same document and they are never differentiated based on long/short-term or other distinctions).

[4] "Causal impact" (or "causal effect") in the counterfactual impact evaluation (CIE) literature is defined as the effect produced by a program intervention in terms of the difference between the before-after-intervention change in a result indicator and the counterfactual change of the same result indicator in the same period (this is the spontaneous change due to factors independent from the program intervention). Under this CIE definition, "impact" referrers to the causal estimation of the part of the change in the result indicator that was 'produced' by the intervention, separately from the spontaneous change that would occur also in the absence of the intervention. This is unlike the definition of the Evaluation Network of DAC-OECD, in which "impact" is referred to as "positive and negative, primary and secondary long-term effects produced by a development intervention". This latter definition of impact is related to both a type of result indicator (that has

Figure 1: Naïf Result-Indicator Analysis

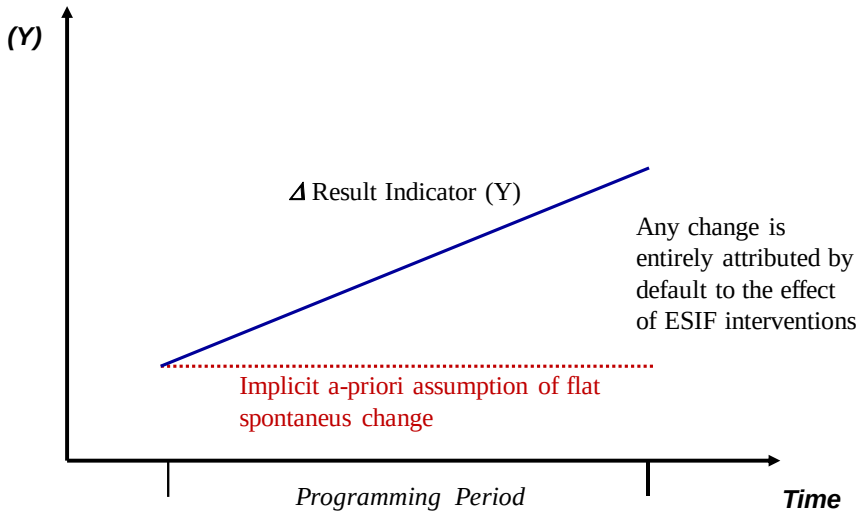
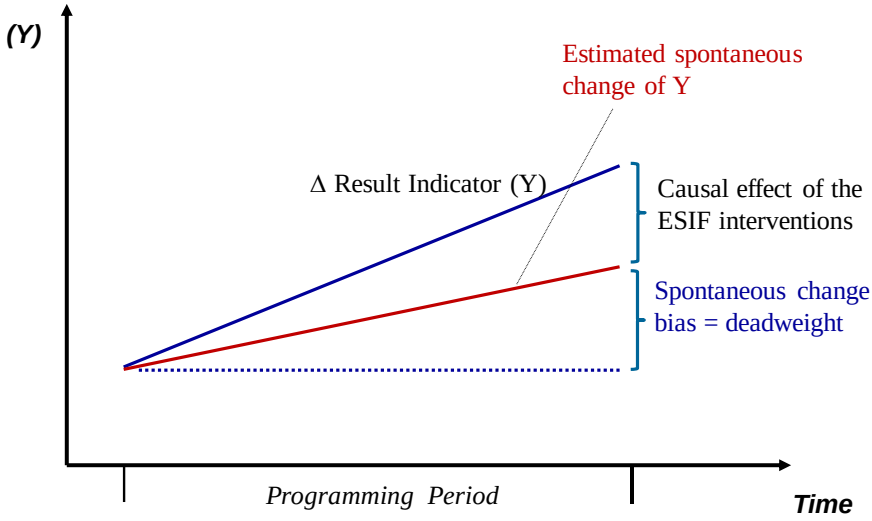


Figure 2: Causal-Effect Analysis of Result Indicators



This is because estimating the spontaneous change of Y that would also occur in the absence of the ESIF support would entail to acquire data on units of observations with similar characteristics and with no ESIF support. In the case of data aggregated at the regional or national level this is a nearly impossible tasks: EU member states and regions tend to have unique features and to receive some support from ESIF, so that no comparable "non-treated units" can be found for the analysis.

For this reason, producing reliable "causal impact" estimates of the effects of the ESIF interventions on nationally (or regionally) aggregated result indicators has inherently a low degree of internal validity. This is not due to shortcomings of the currently available

to be measured in the long term) and the fact that such a change is "produced" by the program intervention. Under the CIE definition, instead, an "impact" is not a specific type of result indicator, but it is a change on any type of result indicators (also short-term ones) that was caused by the programme intervention, separately from the spontaneous change.

methodological tools. Rather, it is because rigorously estimating casual effects is proven to be scientifically unfeasible in a scenario in which there are no adequate data sources of comparable units of observation unexposed to the interventions that are sufficiently similar to the treated units. When this happens there is no way around but to accept that the empirical evidence will have limitations. This circumstance is not yet fully adequately considered in many evaluation designs of ESIF interventions: there is indeed a clear trade-off between the rigour of the internal validity of the analysis and the level of aggregation of the result indicators. The more the evaluation is focused on broad thematic objects at the national level, the less rigorous is the level of internal validity in estimating true causal effects of the ESIF interventions. The more the analysis focuses on more specific interventions at a micro-level the more likely it is that the impact identification conditions will be more favourable and the degree of internal validity of the causal effect estimations will be higher.

Due to such difficulties, for these thematic objective evaluations of ESIF interventions, the available options that have been explored in ToR documents (in an effort to move away from naïf result-indicator analyses), are in terms of: A) Meta-analyses of existing evaluation studies or scientific papers; B) the use of use of experts / expert panels. These two options can provide findings suitable for formulating a judgment on what part of the change in the result indicators is due to the ESIF and what part is due instead to spontaneous change or "deadweight". Causal estimations that rely on expert opinions (or opinions gathered from in in-depth field surveys), however, are hard to be consistently replicated and this could lead to inconsistencies in comparing the findings of different thematic-objective evaluations across different programming periods or different areas of interventions. The same can apply also to meta-analysis estimations: in this case the assessment of the "causal effect" will be based on the pooling together existing evaluations that could form a puzzle of many different degrees of reliability in the causal estimations and many different sources of the evidence (e.g. quasi-experimental CIEs, other econometric/statistical models, predictions from theory of change, opinions from key actors, etc.).

This technical note presents an empirical approach, called "Cross-Regional Sequential Difference-in-Difference" (CR-SEQDD), for providing some evidence on TO evaluations of ESIF interventions aggregated at the national level[5]. The intuitive idea behind this CR-SEQDD approach is to exploit the cross-sectional variation in the intensities of the OP interventions (pertaining to a same TO) that can be recorded regionally (within a same programming period) in order to estimate (controlling for regional differences) a set of parameters that are subsequently used at the national level to establish what part of a change in the relevant result indicator (Y) is likely to be caused by the ESIF support and what part is instead caused by spontaneous change. This can be done by comparing, with a difference-in-difference (DD) scheme, the before-after treatment change of Y recorded in the regions with higher intensities of the ESIF support to the change of Y recorded in the regions with lower intensity of ESIF support. These DD

[5] In the existing literature, sequential difference in difference models have been previously used in the context of a dynamic temporal sequences of program interventions (Ding and Lehrer 2010). However, a part form exploiting repeated DD comparisons, the approach discussed in this technical note focuses on cross-sectional sequences of DD comparisons and shares little similarities with the temporally-sequential difference in difference models.

comparisons can be performed sequentially (in a cross-sectional meaning) for each pair of regions, following an ascending order of the intensity of the ESIF support. If the latter was indeed the major factor in affecting the nationally-recorded before-after-intervention change of Y, these sequential DD comparisons should show that a more positive change of Y is recorded in the regions with higher intensities of ESIF support than in the regions with lower intensity of the support. If this is not the case, instead, it would be more likely that the nationally-recorded change of Y was the result of a spontaneous change that would have been recorded even in the absence of the program intervention.

As described in detail in the next section, the internal validity of the CR-SEQDD estimates holds only under very strict causal identification assumptions and the approach combines together different standard econometric tools that have been in existence for decades, with known limitations in the range of applicability. For these reasons, by all means, the CR-SEQDD approach should not be regarded as a breakthrough methodological tool that produces findings with the same strong internal validity as a standard quasi-experimental approach implemented under more favourable scenarios in terms of causal identification conditions. Unlike experts' opinions and meta-analyses, however, CR-SEQDD offers the advantage of being a fully replicable empirical tool, enabling a consistent comparison of the findings across different times and areas of interventions when it comes to performing TO evaluations of the OP interventions aggregated at the national level. Even if the approach has obvious limitations, it does represent a way of offering evidence that is indeed informative in terms of allowing reliable comparisons of the findings across different thematic areas, programming periods and/or EU countries (the same identical strict casual identification assumptions would apply to the evaluations of different thematic areas, periods and or EU countries, enabling a suitable comparison of the results)[6]. Moreover, CR-SEQDD is deliberately set to be a fairly simple empirical tool, in order to make it possible to be applied at large also in non-academic settings, highlighting in a straightforward and transparent way the data requirements, strong limitations and causal identification assumptions necessary for the estimation.

2. CR-SEQDD PROPERTIES, CAUSAL IDENTIFICATION CONDITIONS AND DATA REQUIREMENTS

The CR-SEQDD approach presented in this technical note can be implemented under the following circumstances and data availability scenarios:

-The intensities of the OP interventions pertaining to a same TO are measurable and they can be allocated at the regional level within the programming period of interest;

-OP interventions and result indicators (Y) are measured in terms of intensities defined with respect to a same baseline size-indicator that captures obvious scale effects that

[6] In addition, as previously mentioned, the limitations of the method do stem from the harsh causal identification conditions posed by these broad thematic objects. Under the same circumstances, no other alternative empirical tool would be able to relax such very strict casual identification assumptions.

may influence the absolute value of the change of Y. For example, number of residents, or residents with higher-education degree: OP intensity = (TO 1 support)/ (residents); Y=(patent applications) / (residents). This baseline size-indicator controls for scale-effect differences among regions that can lead to obvious different potentials for the absolute changes of Y along the estimation period of interest.

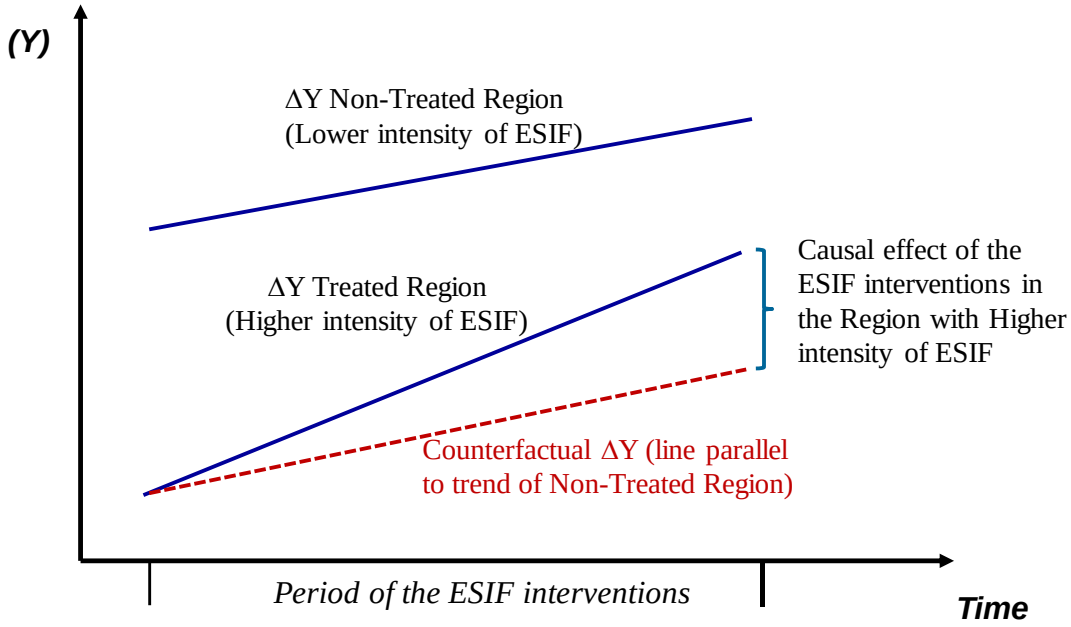
-Across the different regions of the EU member state/s considered in the analysis, the intensities of the ESIF supported OP interventions (pertaining to a same TO) have a sufficiently large degree of variation. As illustrated more in detail in the next sections, this is a necessary condition for the CR-SEQD estimates to achieve standard errors and confidence intervals that are of limited size, enabling the results to be sufficiently informative;

-The regional-level data on the result indicator(s) Y have to cover at least the beginning and the end of the programming period/s of interest;

At the heart of this CR-SEQDD approach are the pairwise difference in difference (DD) schemes that sequentially (along the cross-sectional order of the regions based on the treatment intensity) compare the before-after-intervention cross-regional change of Y. In these pairwise cross-regional DD comparisons, the before-after-intervention change of Y recorded in the low-intensity region are assumed to be the counterfactual change that would be recorded in the higher-intensity regions in the presence of a lower intensity of the treatment. This assumption requires a very strict causal identification condition in terms of cross-regional differences of the relevant baseline characteristics that have to be fixed effects: factors that exert a constant over-time effect on the levels of Y recorded in the subsequent units of time, rather than determining multiplier effects on the future levels of Y. In the DD literature (e.g. Moffit 1991, Lechner 2011, Angrist and Pischke 2009, Card and Krueger 1994, 2000) this casual identification condition is referred to as the "parallel trend assumption" (Figure 3): if exposed to similar intensities of the OP interventions (or in the absence of any OP intervention) regions are free to achieve different levels of Y (based on their different baseline factors) but they have to display similar growth trend of Y (due to the fact that the different baseline factors are assumed to be fixed effects that, as such, have no influence on the changes of Y over time)[7].

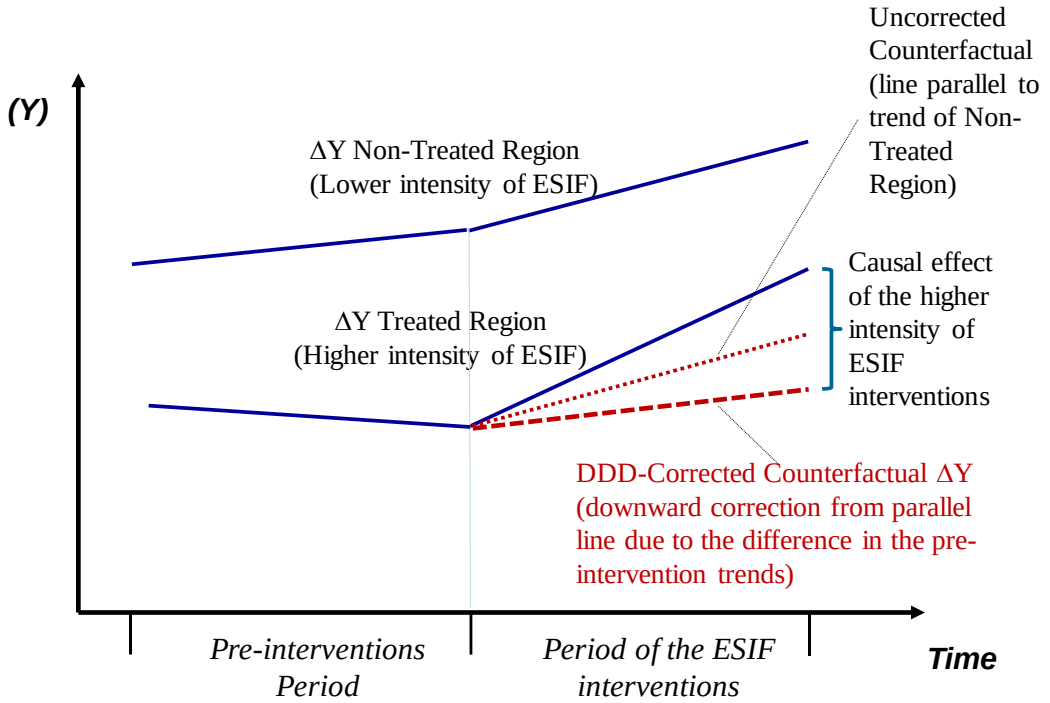
[7] The fixed-effect /parallel-trend condition assumed by the DD schemes can be further explained by means of the following example. Suppose that Region A (receiving a low intensity of OP interventions) is structurally different than region B (higher intensity of the OP interventions). For example, the R&D capacity of Region A is higher than Region B because Region A has more universities, larger number of existing R&D labs and facilities, stronger concentration of residents with higher education. These structural differences between Region A and Region B, entails that Region A tends to have, in any given year, an higher value of a result indicator Y (e.g. n. of patent applications) than Region B. Under this scenario, in a standard quasi-experimental CIE setting, in order to obtain causal estimates of the OP interventions it would be required to find a comparison group of other regions with very similar structural characteristics of region A and B, but different intensities of treatment (or no treatment at all). With a DD comparison, instead, the way in which the different structural characteristics of the regions is taken into account in the analysis is by means of transforming the values of result indicator Y into changes between the beginning and the end of the OP interventions (e.g. 2014-2020). The rationale behind this empirical option is the following: if the differences between the two regions are structural characteristics, these different features may be elements that are constantly in existence in any given year during the 2014-2020 period considered in the analysis (e.g. if one Regions has a larger number of universities this feature tend to be always in existence). For this reason, these structural characteristics, in the DD methodological literature, are referred to as "fixed effects". These fixed effects by definition do have an influence on the levels of result indicator Y (e.g. yearly number of pro-capita patent applications), but they cannot have an influence on the change of Y between different years (these "fixed effects" are always in existence and therefore they cannot induce a change in Y between different periods).

Figure 3: Difference-in-Difference (DD) Cross-Regional Comparisons



In the case where the estimation period can be extended to include one additional pre-intervention time, in which the regional units of observation are all unexposed to the treatment (or exposed to a treatment of the same intensity), the CR-SEQDD model can be estimated with a difference-in-difference-in-difference scheme (DDD, e.g. Moffit 1991, Bondonio 2000, Lechner 2011). In this case, the required causal identification condition would be less stringent, requiring that the treatment and control units would display growth trends of Y that are similar only once adjusted for the treatment-control differences in the growth of Y recorded on the previous period (Figure 4).

Figure 4: Difference-in-Difference-in-Difference (DDD) Cross-Regional Comparisons



Other assumptions that are required by CR-SEQDD are in the following terms:

-The result indicators (Y) have to be affected solely by the OP interventions pertaining to the TO considered in the analysis and not by the OP interventions pertaining to other TOs not included in the analysis;

-The spatial spillovers produced by the OP interventions considered in the analysis have to be contained within the same region in which they are implemented, rather than spanning across different regions;

-The marginal return on Y of each additional unit of intensity of the OP interventions is constant both cross-regionally and across the different values of the treatment intensity within the estimation period considered in the analysis. This assumption is necessary, as explained more in detail in the next section, because the differences in the treatment intensities across the different regions have to be pooled together in the final step of the analysis, regardless of the baseline level of treatment intensity.

3. ESTIMATION PROCEDURE

In simple terms, the CR-SEQDD estimation procedure can be summarized by means of the following steps:

A) The before-after-intervention trend of the result indicator (Y) of interest for the analysis and the intensity of the OP interventions belonging to the pertaining thematic objective (TO) are recorded for each region;

B) Regions are sorted in ascending order of the intensity of the OP interventions [i.e. the treatment (T)] pertaining to the thematic objective (TO) considered in the analysis;

C) Sequentially, along the order of the treatment intensity, a series of pairwise cross-regional difference-in-difference (DD) comparisons [or DDD comparisons if allowed by the data availability scenario] are implemented. The results from these DD or DDD pairwise comparisons are in terms of casual impact parameters (*DDY*) or (*DDDY*) that (with all the limitations posed by the very strict impact identification assumptions mentioned in the previous section) estimate the degree by which an higher intensity of the OP interventions (compared to the baseline of the region with the lower intensity) generate a positive change of Y;

D) The results from each pairwise cross-regional DD comparison are displayed in a two-way scatter plot that contains on the vertical axis the causal impact parameters *DDY* and on the horizontal axis the corresponding difference of treatment intensity (ΔT) between the pair of regions;

E) Based on the two-way scatter plot chart D), a linear or quadratic dose-response function is fitted and estimated in terms of $DDY = \alpha + \beta \Delta T + \varepsilon$ *(1)* or $DDY = \alpha + \beta \Delta T + \chi (\Delta T)^2 + \varepsilon$ [8] (2). Under the strict assumption of a constant marginal return of T

[8] The standard errors of the coefficient estimates of these models have to be obtained with a suitable bootstrapping procedure that takes into account the non-independence of the clusters of DD comparisons involving a same region (e.g. Gonçalves and White 2005, Chen and Onnela 2019).

(as mentioned in the previous section), this linear (1) or quadric function (2)[9] is then used to predict what would be the expected contribution on *DDY* of the ΔT registered at the national level in the period of interest, compared to a scenario of absence of treatment (i.e. ΔT=c, with c=nationally-recorded intensity of the OP interventions);

F) The predicted *DDY* value ($\widehat{DDY}$), estimated in step E) for the nationally-recorded intensity of the OP interventions, is then compared with the raw change (ΔY) of the result indicator recorded nationally in the period of interest. When $\widehat{DDY}$ reaches similar values of ΔY, the CR-SEQDD findings are indicative of a causal impact of the OP interventions being responsible for most of the nationally-recorded ΔY. When $\widehat{DDY}$ is largely lower than ΔY, the CR-SEQDD findings are indicative of a strong component of spontaneous change being responsible for most of the nationally-recorded ΔY[10].

Under ideal data availability conditions (detailed in the application examples described in the next section), the $\widehat{DDY}$ estimates from the final step F) of the analysis are capable of highlighting (with adequate statistical precision) the fraction of the nationally recorded ΔY that is deemed to be caused by the OP interventions, and, conversely, the fraction that is instead caused by spontaneous change. Because of the very strict causal identification assumption required by CR-SEQDD, however, the estimated results are best to be reported also in terms of 95% confidence intervals of the $\widehat{DDY}$ estimated at the nationally recorded intensity of the OP interventions, rather exclusively as single-point estimates.

4. APPLICATION EXAMPLES

This section presents four application examples of the CR-SEQDD estimation procedure [steps A)-F), described above]. For ease of comparability, all examples are related to the evaluation of nationally-aggregated OP interventions pertaining to Thematic Objective (TO) 1, *Strengthening research, technological development and innovation*. The sample of regions is *N=15*, and the available regional-level data concerns:

$\Delta Y_i = (Y_{ipost} - Y_{ipre})$ = Pre-post-intervention change in the yearly number of patent applications per million of residents recorded in region (*i*) [*t=pre* (pre-intervention year) and *t=post* (post-intervention year]][11];

[9] In principle, more complex functional forms could be also considered in the case that they ensure a better fit of the data. Due to the small number of regions that are often available for the analysis, however, a more parsimonious functional form is likely to be preferable, in most cases, for preserving the statistical efficiency of the estimated parameters of the model.

[10] As an alternative to the estimation procedure A)-F), in some circumstances, a function $\Delta Y=f(T)$ can be fitted and estimated directly on the two-way plot chart of the regional distribution of T and ΔY. The estimated parameters from $\Delta Y=f(T)$ can be used to find the predicted value of ΔY corresponding to the nationally recorded level of T. In this case, the estimated contribution of the nationally-recorded intensity of the OP interventions (T=c) on the pre-post-intervention change of the result-indicator (ΔY) is obtained as the difference between the predicted values of ΔY corresponding to T=c, and T=0. This option generally entails a lower statistical efficiency of the estimation, but avoids the issues of non-independence of the observations in estimating the standard errors of the model.

[11] For easy of simplicity, the application examples focus on cross-regional DD comparisons, instead of DDD comparisons. These application examples, however, can be easily extended to include DDD comparisons when the available data do include, in addition to $\Delta Y=(Y_{post}-Y_{pre})$, also the changes of Y recorded along a previous period of observation [i.e. $\Delta(Y_{pre}-Y_{pre-1})$] in which all

T_i= Per-capita intensity of the ESIF monetary resources spent in the (pre-post) period for all the OP interventions pertaining to TO1.

Example I): Ideal data-availability scenario, strong causal effect of the OP interventions

In the following example I), the regional data available for the analysis (Table 1) are ideal because of the very high amplitude of the cross-regional variation of T (Table 1).

Table 1:
Intensities of OP interventions (T) and patent applications (Y) per million of residents

Region	Pop.	TO1 OP support (1=€Mil.)	T [Intensity of TO1 support] 1 = (1 €Mil.) / (Mil. Residents)	Y_{pre} 1= No. Pat. Appl. / Mil. Residents	Y_{post} 1= No. Pat. Appl. / Mil. Residents	ΔY = (Y_{post}) - (Y_{pre})
A	500,000	0	0	65.5	66.0	0.5
B	1,200,000	24	20	58.4	62.8	4.4
C	800,000	36	45	55.3	64.1	8.8
D	2,400,000	120	50	52.3	62.0	9.7
E	3,000,000	165	55	50.1	60.8	10.7
F	1,400,000	86.8	62	48.6	61.2	12.6
G	2,000,000	130	65	53.5	66.7	13.2
H	1,500,000	102	68	52.3	65.7	13.4
I	2,200,000	154	70	55.7	69.8	14.1
L	1,200,000	88.8	74	58.9	73.5	14.6
M	600,000	45.6	76	60.2	75.3	15.1
N	1,400,000	109.2	78	56.4	71.8	15.4
O	2,000,000	160	80	57.3	73.5	16.2
P	1,100,000	93.5	85	60.1	76.9	16.8
Q	1,600,000	137.6	86	56.3	73.7	17.4
Nation	22,900,000	1452.5	63.4	54.8	67.5	12.7

Source: data generated for exemplification purposes

regions were not exposed to the same OP interventions considered in the analysis, or to a constant-across-regions intensity of the OP interventions.

Indeed the national average level of T (=intensity of the OP interventions =€ 63.4 Million / Million of residents) is smaller than the (max, min) difference across the regional values of T and the standard deviation of the regional values of T is more than 1/3 of the national average level of T. Under this circumstances, the national intensity of T is inside the common support of the regional variations of T.

Table 2 contains the results of the pairwise cross-regional sequential (DD) estimations, while Table 3 illustrates the related pairwise cross-regional changes in the treatment intensity.

Table 2:
Pairwise Difference-in-difference variations (DDY) between Comparison and Baseline Regions

	Baseline Region (Lower T)															
Comparison Region (Higher T)		A	B	C	D	E	F	G	H	I	L	M	N	O	P	Q
	A	-														
	B	3.9	-													
	C	8.3	4.4	-												
	D	9.2	5.3	0.9	-											
	E	10.2	6.3	1.9	1	-										
	F	12.1	8.2	3.8	2.9	1.9	-									
	G	12.7	8.8	4.4	3.5	2.5	0.6	-								
	H	12.9	9	4.6	3.7	2.7	0.8	0.2	-							
	I	13.6	9.7	5.3	4.4	3.4	1.5	0.9	0.7	-						
	L	14.1	10.2	5.8	4.9	3.9	2	1.4	1.2	0.5	-					
	M	14.6	10.7	6.3	5.4	4.4	2.5	1.9	1.7	1	0.5	-				
	N	14.9	11	6.6	5.7	4.7	2.8	2.2	2	1.3	0.8	0.3	-			
	O	15.7	11.8	7.4	6.5	5.5	3.6	3	2.8	2.1	1.6	1.1	0.8	-		
	P	16.3	12.4	8	7.1	6.1	4.2	3.6	3.4	2.7	2.2	1.7	1.4	0.6	-	
	Q	16.9	13	8.6	7.7	6.7	4.8	4.2	4	3.3	2.8	2.3	2	1.2	0.6	-

1= [No. Pat. Appl. / Mil. Residents] in terms of pairwise Difference-in-difference variation of Y (DDY) between Comparison and Baseline Regions

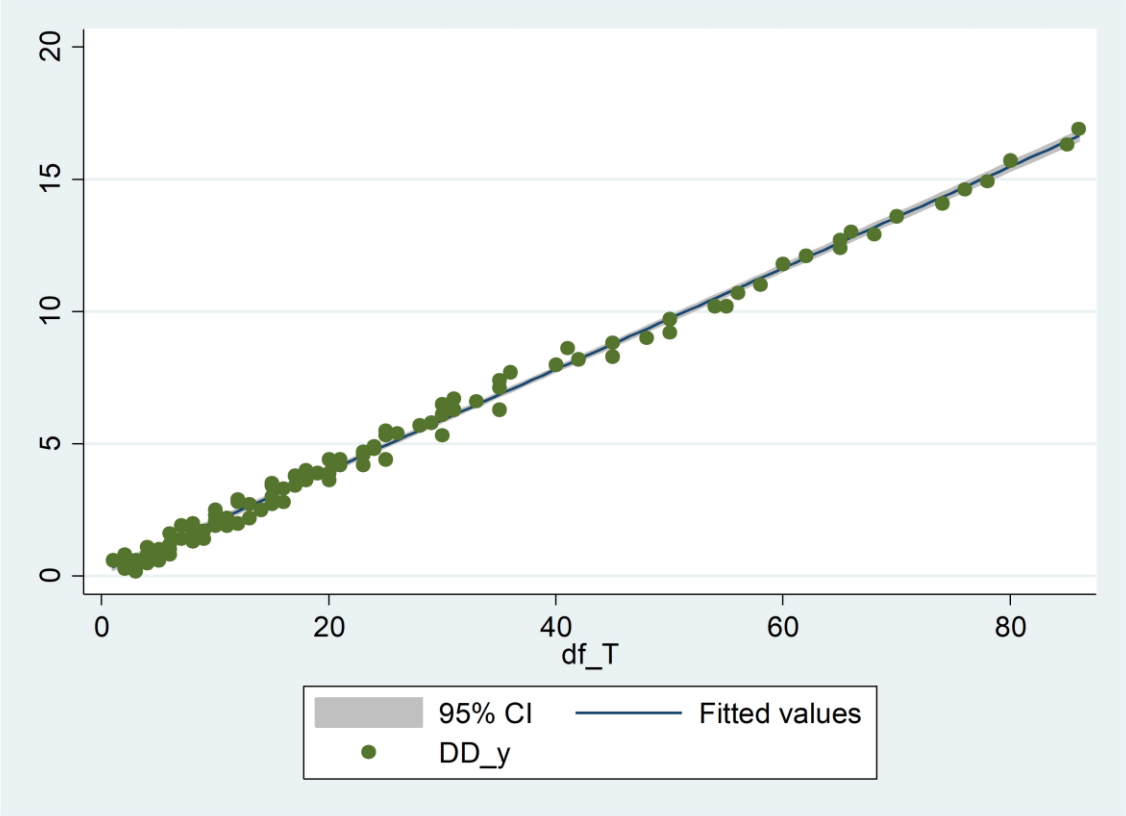
Table 3:
Pairwise Cross-Regional Differences in the Intensities of the OP Interventions (ΔT)

		Baseline Region														
Comparison Region		A	B	C	D	E	F	G	H	I	L	M	N	O	P	Q
	A	-														
	B	20	-													
	C	45	25	-												
	D	50	30	5	-											
	E	55	35	10	5	-										
	F	62	42	17	12	7	-									
	G	65	45	20	15	10	3	-								
	H	68	48	23	18	13	6	3	-							
	I	70	50	25	20	15	8	5	2	-						
	L	74	54	29	24	19	12	9	6	4	-					
	M	76	56	31	26	21	14	11	8	6	2	-				
	N	78	58	33	28	23	16	13	10	8	4	2	-			
	O	80	60	35	30	25	18	15	12	10	6	4	2	-		
	P	85	65	40	35	30	23	20	17	15	11	9	7	5	-	
	Q	86	66	41	36	31	24	21	18	16	12	10	8	6	1	-
1= [€Mil / Mil. Residents] in terms of cross-regional pairwise differences of OP-intervention intensities.																

The two-way scatter plot chart of Figure 5 contains on the vertical axis the DD estimates from the pairwise cross-regional comparisons of ΔY (Table 2), and on the horizontal axis the corresponding pairwise differences across the regional OP-intervention intensities (ΔT), Table 3.

The data of the scatter plot chart of Figure 5 are perfectly fitted by a linear dose-response functional form in terms of $DDY = \alpha + \beta \Delta T + \varepsilon$ that is estimated with OLS and a suitable bootstrap procedure for the standard errors and related confidence intervals.

Figure 5:
Two-way Scatter Plot Chart
Vertical Axis=Pairwise Cross-Regional Causal Impact Estimations DDY
Horizontal Axis=Pairwise Cross-Regional Variation of Treatment Intensity (ΔT)



The estimated parameters of the linear dose-response function are:

```
Number of obs      =       105
Wald chi2(1)       =   1398.59
Prob > chi2        =    0.0000
R-squared          =    0.9945
Adj R-squared      =    0.9945
Root MSE           =    0.3171
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ΔT |   .1915361   .0051216    37.40   0.000      .181498    .2015743
           α |   .1524562   .1015183     1.50   0.133     -.046516    .3514285
```

Based on these parameters, the predicted value ($\widehat{DDY}$) for the nationally-recorded intensity of the OP interventions, is estimated as: 0.1525 + 0.1915 * 63.4 =12.3 (additional number of yearly patent applications per million of residents caused nationally by an intensity of € 63.4 Million worth of OP interventions in TO 1). The 95% confidence interval of such $\widehat{DDY}$ predicted values is estimated as [+11.46, 13.13][12].

[12] 11.46 = (-0.046516 +0.1815*63.4); 13.13 = (0.3514285+0.2015743*63.4).

This result produced by the CR-SEQDD model, when compared to the nationally–recorded raw change of the result indicator Y ($\Delta Y = +12.7$, Table 1), indicates that the OP interventions were likely to be responsible for almost all of the of before-after-intervention change in the result indicator Y, with a minimal role played by spontaneous change in affecting such change.

Example II): Ideal data availability scenario, absence of causal effect of the OP interventions

In the following example II), the regional data (Table 4) are the same as in example I) as regards the intensities of the OP interventions. In terms of the regional values of ΔY, instead, the data are not favourable for the finding of a strong causal effect of the OP interventions.

Table 4:
Intensities of OP interventions (T) and patent applications (Y) per million of residents

Region	Pop.	TO1 OP support (1=€Mil.)	T [Intensity of TO1 support] 1 = (1 €Mil.) / (Mil. Residents)	Y_{pre} 1= No. Pat. Appl. / Mil. Residents	Y_{post} 1= No. Pat. Appl. / Mil. Residents	$\Delta Y = (Y_{post}) - (Y_{pre})$
A	500,000	0	0	65.5	70.0	4.5
B	1,200,000	24	20	58.4	62.5	4.1
C	800,000	36	45	55.3	59.5	4.2
D	2,400,000	120	50	52.3	56.1	3.8
E	3,000,000	165	55	50.1	54.6	4.5
F	1,400,000	86.8	62	48.6	54.7	6.1
G	2,000,000	130	65	53.5	59.1	5.6
H	1,500,000	102	68	52.3	56.6	4.3
I	2,200,000	154	70	55.7	59.9	4.2
L	1,200,000	88.8	74	58.9	65.0	6.1
M	600,000	45.6	76	60.2	64.3	4.1
N	1,400,000	109.2	78	56.4	61.2	4.8
O	2,000,000	160	80	57.3	62.7	5.4
P	1,100,000	93.5	85	60.1	64.4	4.3
Q	1,600,000	137.6	86	56.3	61.0	4.7
Nation	22,900,000	1452.5	63.4	54.8	59.5	4.7

Source: data generated for exemplification purposes

Similarly as in the previous example, Table 5 contains the results of the pairwise cross-regional sequential (DD) estimations, while Table 6 illustrates the related pairwise cross-regional changes in the treatment intensity.

Table 5:
Pairwise Difference-in-difference variations (DDY) between Comparison and Baseline Regions

		Baseline Region (Lower T)														
		A	B	C	D	E	F	G	H	I	L	M	N	O	P	Q
Comparison Region (Higher T)	A	-														
	B	-0.4	-													
	C	-0.3	0.1	-												
	D	-0.7	-0.3	-0.4	-											
	E	0.0	0.4	0.3	0.7	-										
	F	1.6	2.0	1.9	2.3	1.6	-									
	G	1.1	1.5	1.4	1.8	1.1	-0.5	-								
	H	-0.2	0.2	0.1	0.5	-0.2	-1.8	-1.3	-							
	I	-0.3	0.1	0.0	0.4	-0.3	-1.9	-1.4	-0.1	-						
	L	1.6	2.0	1.9	2.3	1.6	0.0	0.5	1.8	1.9	-					
	M	-0.4	0.0	-0.1	0.3	-0.4	-2.0	-1.5	-0.2	-0.1	-2.0	-				
	N	0.3	0.7	0.6	1.0	0.3	-1.3	-0.8	0.5	0.6	-1.3	0.7	-			
	O	0.9	1.3	1.2	1.6	0.9	-0.7	-0.2	1.1	1.2	-0.7	1.3	0.6	-		
	P	-0.2	0.2	0.1	0.5	-0.2	-1.8	-1.3	0.0	0.1	-1.8	0.2	-0.5	-1.1	-	
	Q	0.2	0.6	0.5	0.9	0.2	-1.4	-0.9	0.4	0.5	-1.4	0.6	-0.1	-0.7	0.4	-

1= [No. Pat. Appl. / Mil. Residents] in terms of pairwise Difference-in-difference variation of Y (DDY) between Comparison and Baseline Regions

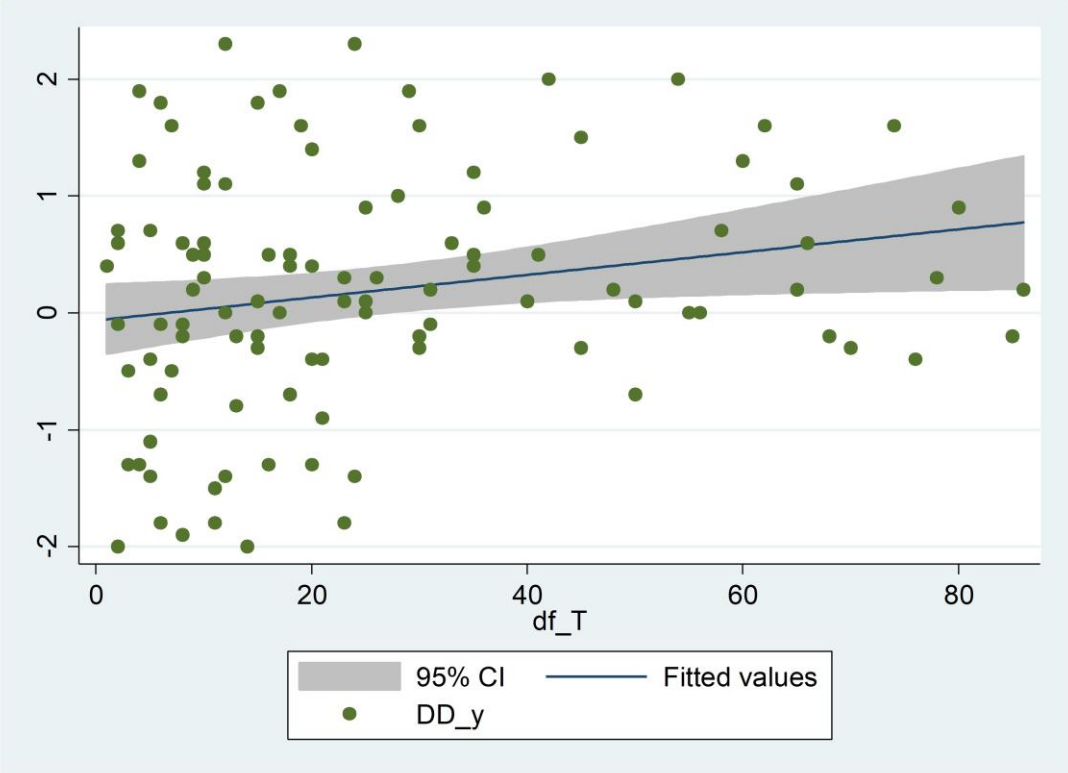
Table 6:
Pairwise Cross-Regional Differences in the Intensities of the OP Interventions (∆T)

		Baseline Region														
		A	B	C	D	E	F	G	H	I	L	M	N	O	P	Q
Comparison Region	A	-														
	B	20	-													
	C	45	25	-												
	D	50	30	5	-											
	E	55	35	10	5	-										
	F	62	42	17	12	7	-									
	G	65	45	20	15	10	3	-								
	H	68	48	23	18	13	6	3	-							
	I	70	50	25	20	15	8	5	2	-						
	L	74	54	29	24	19	12	9	6	4	-					
	M	76	56	31	26	21	14	11	8	6	2	-				
	N	78	58	33	28	23	16	13	10	8	4	2	-			
	O	80	60	35	30	25	18	15	12	10	6	4	2	-		
	P	85	65	40	35	30	23	20	17	15	11	9	7	5	-	
	Q	86	66	41	36	31	24	21	18	16	12	10	8	6	1	-

1= [€ Mil. / Mil. Residents] in terms of cross-regional pairwise differences of OP-intervention intensities.

The two-way scatter plot chart of Figure 6 contains on the vertical axis the DD estimates from the pairwise cross-regional comparisons of ∆Y (Table 5), and on the horizontal axis the corresponding pairwise differences across the regional OP-intervention intensities (∆T, Table 6).

Figure 6:
Two-way Scatter Plot Chart (Linear Fitting)
Vertical Axis=Pairwise Cross-Regional Causal Impact Estimations DDY
Horizontal Axis=Pairwise Cross-Regional Variation of Treatment Intensity (T)

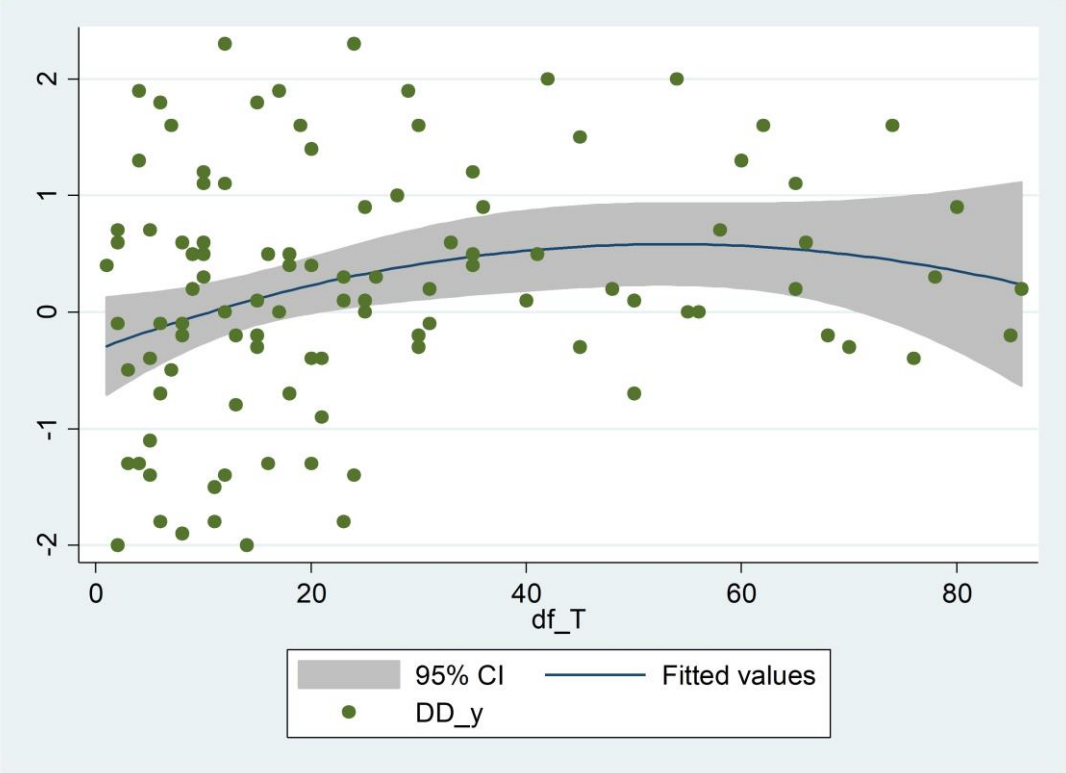


The estimated parameters of the linear dose-response function fitted on the data of Figure 6 are:

```
Number of obs      =       105
Wald chi2(1)       =      1.27
Prob > chi2        =    0.2600
R-squared          =    0.0439
Adj R-squared      =    0.0346
Root MSE           =    1.0153
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ΔT |   .0097267   .0086355     1.13   0.260    -.0071984    .0266519
           α |  -.0635309    .343532    -0.18   0.853    -.7368413    .6097794
------------------------------------------------------------------------------
```

Figure 7 illustrates the quadrating fitting model on the same cross-sectional DD comparisons and ΔT data.

Figure 7:
Two-way Scatter Plot Chart (Quadratic Fitting)
Vertical Axis=Pairwise Cross-Regional Causal Impact Estimations DDY
Horizontal Axis=Pairwise Cross-Regional Variation of Treatment Intensity (T)



The estimated parameters of this quadratic dose-response function are:

```
Number of obs      =       105
Wald chi2(2)       =      3.26
Prob > chi2        =    0.1963
R-squared          =    0.0670
Adj R-squared      =    0.0487
Root MSE           =    1.0079
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ΔT |   .0341292   .0234206     1.46   0.145    -.0117744    .0800328
       (ΔT)² |  -.0003206    .000429    -0.75   0.455    -.0011615    .0005203
           α |  -.3249222   .3914696    -0.83   0.407    -1.092189    .4423441
------------------------------------------------------------------------------
```

The estimated coefficients of both the linear and the quadratic functional forms have large standard errors and are not statistically significant at the 0.05 level. Based on these parameters, the predicted value ($\widehat{DDY}$), estimated at the nationally-recorded intensity of the OP interventions (ΔT), is close to zero, with a point estimation that, for both functional forms, is equal to +0.55 (additional number of yearly patent applications per million of residents caused nationally by an intensity of €63.4 Million worth of OP interventions in TO 1). Because of the very large standard errors of the coefficient

estimates, the related 95% confidence interval of this ($\widehat{DDY}$) predicted value is also extremely ample for both functional forms.

Because in this application example the very large standard errors and corresponding confidence intervals of the results do not stem from a data limitation in terms of insufficient cross-regional variation in the treatment intensities, the CR-SEQDD estimates are conclusive in indicating that the nationally-recorded raw change of the result indicator Y (ΔY=+4.7, Table 4) is most likely due to spontaneous change, and that the causal contribution of the OP interventions is instead minimal.

Example III): Sufficient data-availability scenario, strong causal effect of the OP interventions

In the following example III), the regional data availability scenario (Table 7) is not ideal, but it is still sufficient to enable the CR-SEQDD estimation to produce some indicative findings. This is because the amplitude of the cross-regional variation of T is more limited than in the previous examples I) and II): no regions are untreated, the maximum range of cross-regional variation of T is 34 (€ Million / Million of residents, which is slightly lower than the national average of T = 40.8) and the standard deviation of the regional distribution of T is about 1/4 of the national average level of T. In terms, instead, of the regional values of ΔY, the data used in this example are favourable for the finding of a strong causal effect of the OP interventions.

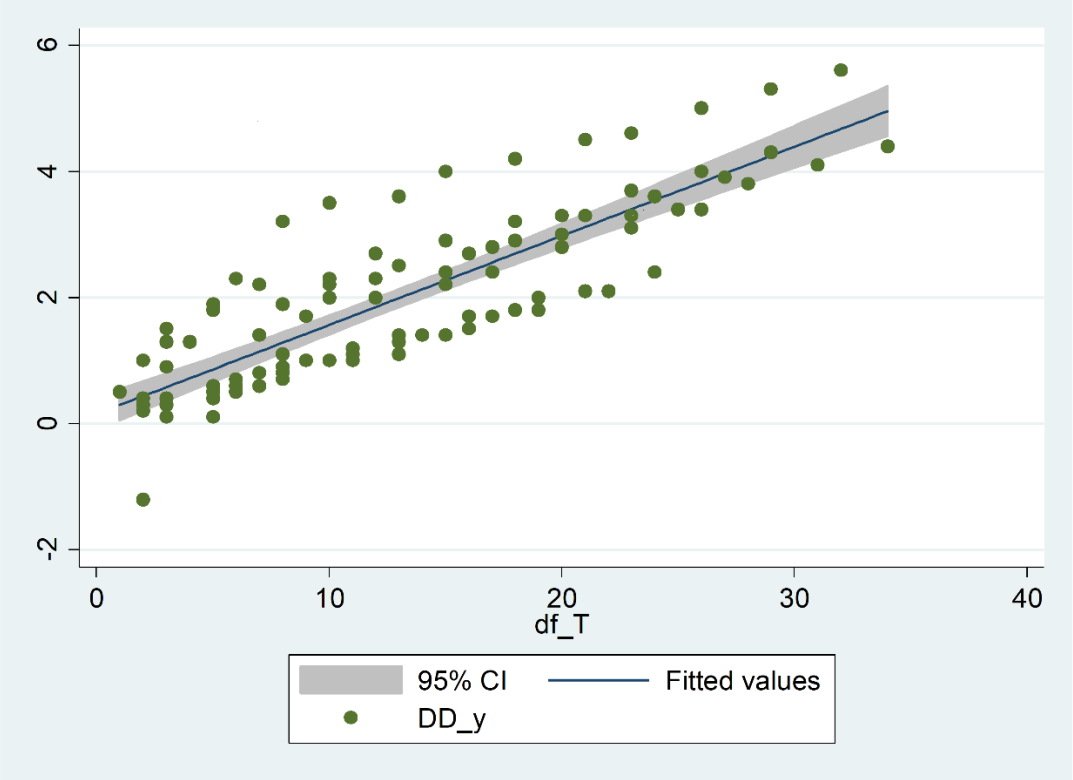
Table 7:
Intensities of OP interventions (T) and patent applications (Y) per million of residents

Region	Pop.	TO1 OP support (1=€Mil.)	T [Intensity of TO1 support] 1 = (1 €Mil.) / (Mil. Residents)	Y_{pre} 1= No. Pat. Appl. / Mil. Residents	Y_{post} 1= No. Pat. Appl. / Mil. Residents	ΔY = (Y_{post}) - (Y_{pre})
A	500,000	12.5	25	65.5	69.8	4.3
B	1,200,000	32.4	27	58.4	61.5	3.1
C	800,000	24	30	55.3	59.7	4.4
D	2,400,000	76.8	32	52.3	57.2	4.9
E	3,000,000	99	33	50.1	55.5	5.4
F	1,400,000	49	35	48.6	54.9	6.3
G	2,000,000	74	37	53.5	60.1	6.6
H	1,500,000	60	40	52.3	59.0	6.7
I	2,200,000	92.4	42	55.7	62.8	7.1
L	1,200,000	54	45	58.9	66.2	7.3
M	600,000	28.8	48	60.2	67.8	7.6
N	1,400,000	70	50	56.4	64.1	7.7
O	2,000,000	106	53	57.3	65.4	8.1
P	1,100,000	61.6	56	60.1	68.5	8.4
Q	1,600,000	94.4	59	56.3	65.0	8.7
Nation	22,900,000	934.9	40.8	54.8	61.3	6.5

Source: data generated for exemplification purposes

Figure 8 illustrates the two-way scatter plot chart, fitted with a linear dose-response function, that contains on the vertical axis the DD estimates from the pairwise cross-regional comparisons of ΔY derived from Table 7, and on the horizontal axis the corresponding pairwise differences across the regional OP-intervention intensities (ΔT).

Figure 8:
Two-way Scatter Plot Chart (Linear Fitting)
Vertical Axis=Pairwise Cross-Regional Causal Impact Estimations DDY
Horizontal Axis=Pairwise Cross-Regional Variation of Treatment Intensity (T)



The estimated parameters of the linear-fitting dose-response function are:

```
Number of obs      =       105
Wald chi2(1)       =    188.22
Prob > chi2        =    0.0000
R-squared          =    0.7182
Adj R-squared      =    0.7155
Root MSE           =    0.7348
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ΔT |   .1412373   .0102946    13.72   0.000     .1210601    .1614144
           α |   .1535672    .166306     0.92   0.356    -.1723867     .479521
------------------------------------------------------------------------------
```

Based on these parameters, the predicted value ($\widehat{DDY}$) for the nationally-recorded intensity of the OP interventions, is estimated as: 0.15356+ 0.141237* 40.8 =5.9 (additional number of yearly patent applications per million of residents caused nationally by an intensity of €40.8 Million worth of OP interventions in TO 1).

Although the standard errors of the dose response parameters (particularly for the intercept α) have larger standard errors than in example I), the 95% confidence interval [+4.77, +7.06] of the $\widehat{DDY}$ predicted values remains such that the findings are indicative of a strong casual effect of the OP interventions. Indeed, when compared to the nationally–recorded raw change of the result indicator Y (ΔY =+6.5, Table 7), the CR-SEQDD estimates indicate that the OP interventions were likely to be responsible for a very large part of the before-after-intervention national change of Y, with a minimal role played by spontaneous change.

Example IV): Sufficient data-availability scenario, weaker causal effect of the OP interventions

In the following example IV), the regional data (Table 8) are the same of the previous example III) for what it concerns the intensities of the OP interventions. In terms of the regional values of ΔY, instead, the data are conducive to estimate a weaker (than example III) causal effect of the OP interventions.

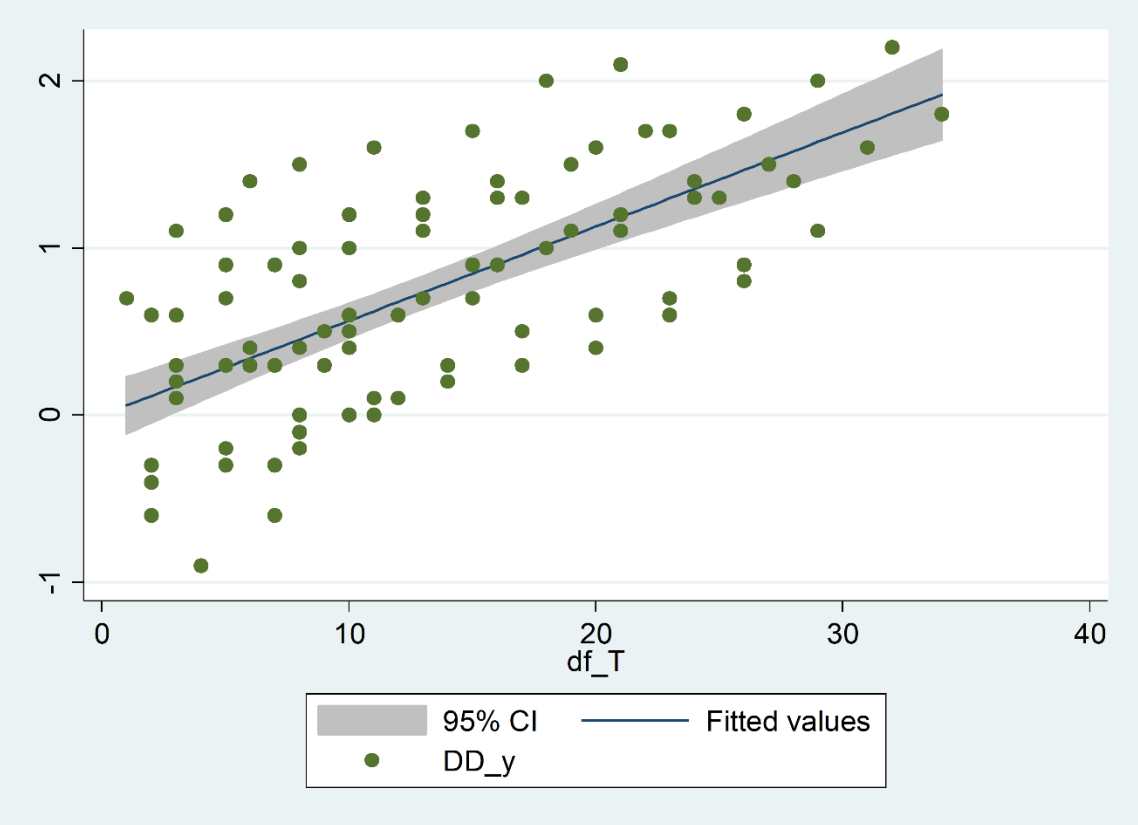
Table 8:
Intensities of OP interventions (T) and patent applications (Y) per million of residents

Region	Pop.	TO1 OP support (1=€Mil.)	T [Intensity of TO1 support] 1 = (1 €Mil.) / (Mil. Residents)	Y_{pre} 1= No. Pat. Appl. / Mil. Residents	Y_{post} 1= No. Pat. Appl. / Mil. Residents	ΔY = (Y_{post}) - (Y_{pre})
A	500,000	12.5	25	65.5	69.0	3.5
B	1,200,000	32.4	27	58.4	61.5	3.1
C	800,000	24	30	55.3	59.5	4.2
D	2,400,000	76.8	32	52.3	56.1	3.8
E	3,000,000	99	33	50.1	54.6	4.5
F	1,400,000	49	35	48.6	52.5	3.9
G	2,000,000	74	37	53.5	57.1	3.6
H	1,500,000	60	40	52.3	56.5	4.2
I	2,200,000	92.4	42	55.7	60.5	4.8
L	1,200,000	54	45	58.9	64.0	5.1
M	600,000	28.8	48	60.2	65.4	5.2
N	1,400,000	70	50	56.4	61.2	4.8
O	2,000,000	106	53	57.3	62.2	4.9
P	1,100,000	61.6	56	60.1	65.2	5.1
Q	1,600,000	94.4	59	56.3	61.6	5.3
Nation	22,900,000	934.9	40.8	54.8	59.2	4.4

Source: data generated for exemplification purposes

Figure 9 describes the two-way scatter plot chart, fitted with a linear dose-response function, that contains on the vertical axis the DD estimates from the pairwise cross-regional comparisons of ΔY derived from Table 8, and on the horizontal axis the corresponding pairwise differences across the regional OP-intervention intensities (ΔT).

Figure 9:
Two-way Scatter Plot Chart (Linear Fitting)
Vertical Axis=Pairwise Cross-Regional Causal Impact Estimations DDY
Horizontal Axis=Pairwise Cross-Regional Variation of Treatment Intensity (T)



The estimated parameters of the linear-fitting dose-response function are:

```
Number of obs      =       105
Wald chi2(1)       =    132.57
Prob > chi2        =    0.0000
R-squared          =    0.4678
Adj R-squared      =    0.4626
Root MSE           =    0.4989
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ΔT |   .0563097   .0048906    11.51   0.000     .0467243    .0658952
           α |   .0024534    .124269     0.02   0.984    -.2411092    .2460161
------------------------------------------------------------------------------
```

Based on these parameters, the predicted value ($\widehat{DDY}$) for the nationally-recorded intensity of the OP interventions, is estimated as: .0024534 + 0.0563097* 40.8 =2.3 (additional number of yearly patent applications per million of residents caused nationally by an intensity of €40.8 Million worth of OP interventions in TO 1).

Although the standard error of the intercept (α) of the dose response model is quite large, the 95% confidence interval [+1.67, +2.94] of the $\widehat{DDY}$ predicted values remains narrow enough to indicate that OP interventions were responsible for about 38%-

66,8%[13] of the pre-post treatment raw change of Y recorded at the national level. The remaining 62%-33.2% of the change of Y is instead estimated to be produced by spontaneous change.

[13] 38%=(1.67 / 4.4) ; 66.8 %= (2.94 / 4.4).

REFERENCES

Angrist, J. D., & Pischke, J. S. (2009), Mostly harmless econometrics: An empiricist's companion, Princeton University Press.

Bondonio D. (2000), "Statistical methods to evaluate geographically-targeted economic development programs", Statistica Applicata, 12, 2, 177-204.

Card, D., & Krueger, A. B. (1994). "Wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania". American Economic Review, 84, 772–793.

Card, D., & Krueger, A. B. (2000). "Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania: reply". American Economic Review, 90, 1397–1420.

Chen S. and Onnela J-P. (2019), "A Bootstrap Method for Goodness of Fit and Model Selection with a Single Observed Network", Nature Research Scientific Reports, 9:16674, https://doi.org/10.1038/s41598-019-53166-6

DingW. and Lehrer S. F. (2010), "Estimating Treatment Effects from Contaminated Multiperiod Education Experiments: The Dynamic Impacts of Class Size Reductions", The Review of Economics and Statistics , 92, 1, pp. 31-42.

Gonçalves S.and WhiteH. (2005), "Bootstrap Standard Error Estimates for Linear Regression", Journal of the American Statistical Association , 100, 471, pp.. 970-979

Lechner, M. (2011). "The estimation of causal effects by difference-in-difference methods". Foundations and Trends® in Econometrics, 4, 165–224.

Moffit R. (1991), Program evaluation with nonexperimental data, Evaluation Review, 15: 291-314.

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