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ABSTRACT

Targeting and Effectiveness of Location-Based Policies*

This paper provides insights into the design of effective location-based policies. In the context of European regional policy, we use algorithms to predict regions that are likely to underutilize funding and identify the key determinants of their low absorptive capacity. We then use a regression discontinuity design (RDD) to document that EU funds are ineffective in recipients predicted to have low absorptive capacity while increasing output and employment in high-capacity regions. Our approach allows early identification and targeting of interventions to increase regional spending capacity based on publicly available data and standard algorithms, thereby facilitating implementation by policymakers.

JEL Classification: C21, F35, H77, R11

Keywords: location-based policies, program design, machine learning

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1. Introduction

There is a renewed interest among economists and policymakers in industrial and territorial policies (Juhász et al. 2023). The theoretical point about the possible market failures that would make these policies desirable is mostly shared (Venables 2024). However, how to concretely design effective policies remains widely debated, even in light of the results of counterfactual evaluations that showcase success along with significant failures. This paper aims to contribute to the literature on the design of location-based programs, using the experience of the European regional policy. Other than being the widest regional policy in the Western world, accounting for almost one-third of the overall EU budget, it is one of the most significant examples of a policy that has been evaluated, with results pointing to a very mixed picture (von Ehrlich and Overman 2020; von Ehrlich 2024). Moreover, there is an ongoing discussion about how to reform cohesion policy to increase its effectiveness.[1]

This paper suggests how to increase effectiveness by improving the targeting of the program. By elaborating on the notion of absorptive capacity (AC, Becker, 2013), it shows that the regions that are able to properly manage funding can be accurately predicted and that for these regions regional aid is effective, as it increases growth and employment. For the areas where local AC is low the program as it stands is unlikely to provide growth or employment benefits; thus, in these cases, regional policy should instead aim at establishing prerequisites for effectiveness, that is enhancing local AC.

More in details, in the first part of the paper we employ machine learning (ML) techniques and proxy absorptive capacity with a measure of expenditure speed. Our algorithmic predictions are derived by using a variety of available methods (Lasso, Random Forest, Neural Network, and Gradient Boosted Machine). Using data from the 2000-06 EU programming period we document that predictions are always very accurate and are the best when the Random Forest algorithm is employed. In the second part of the paper, we employ a sharp Regression Discontinuity Design (s-RDD) that exploits the EU Fund's assignment rule, according to which regions are funded only when their GDP per capita is below 75% of the EU average. We test whether the policy in 2007-2013 EU programming period was effective in boosting GDP growth and employment, conditional on the predicted absorptive capacity of the regions at the beginning of the period. Results confirm that EU money triggers growth and employment only in the regions that exhibit a high level of absorptive capacity, whilst it has no significant impact on low-capacity regions.[2]

Our results highlight the substantial gains associated with ML targeting: more than 50% of resources are currently allocated to regions that cannot fully benefit from them. Bringing regional absorptive capacity up

[1] See, for instance, https://ec.europa.eu/regional_policy/information-sources/cohesion-report_en and https://op.europa.eu/it/publication-detail/-/publication/c6e97287-cee3-11ee-b9d9-01aa75ed71a1/language-en.

[2] Machine learning methods are gaining popularity as a tool to improve policy effectiveness and inform policy decision (Athey 2019; De Lombaerde et al. 2023; Zheng et al. 2023). Closely related to our paper, Hoffman and Mast (2019) focus on the effect of a place-based policy on local crime, whilst Andini et al. (2018) concentrate on a tax rebate scheme aimed at boosting household consumption.

to that of the best-performing regions would lead to an overall improvement in policy effectiveness in terms of GDP and employment growth.

A few aspects of our study are worthy of comment. First, a prominent issue related to the use of algorithms for policy decisions is transparency. Admittedly, the current allocation rule (75% of the average EU GDP per capita) is very understandable and easy to communicate. In this respect, however, an important distinction refers to formal versus substantive transparency. The latter includes being accountable for effectively using public money. Even a complex rule can be transparent if the objective is made explicit and the effectiveness demonstrated. In our case, the current allocation rule ranks high on formal transparency, but it shows drawbacks on the substantive transparency side being poorly effective in low AC regions. Second, our results suggest that the current policy framework needs to be revised. Indeed, we both find that absorptive capacity is not persistent over time and does not reflect the distribution of GDP as one might expect. The regions predicted to be poor users of funds are not only the poorest, and the level of AC varies over the programming period. Improving local AC before funds are delivered may then be an appropriate policy adjustment, which can be done through the provision of technical assistance, through a process of capacity building, or by allowing for additional safeguards. In particular, our study allows for identifying such regions well before funds are disbursed, thus allowing for targeted policy interventions. Finally, it is important to note that our prediction is based on publicly available data and off-the-shelf algorithms. It is therefore easy for policy makers to implement.

The paper is structured as follows. Section 2 presents the prediction analysis. Section 3 documents the gains in effectiveness that could be achieved by using the algorithmic prediction of recipients. Section 4 discusses the potential use of our results for policy purposes and concludes.

2. Targeting absorptive capacity

2.1 Data and Methods

The EU Parliament defines absorptive capacity as 'the extent to which a Member State and its regions are able to spend the financial resources allocated from the Structural and Cohesion Funds effectively and efficiently' (EP 2011, p. 5). It identifies several interrelated factors leading to absorption difficulties, related to i) the complexity of the policy, ii) hierarchical problems between institutions, iii) limited resources - in terms of quality or quantity, iv) inadequate administrative or institutional quality at national or regional level, v) exogenous or political circumstances (ibid., pp. 6-7). We measure absorptive capacity using a proxy that captures a region's ability to spend transfers within the allocated time. This serves as an outcome in our machine learning prediction model. Similar approaches have been used in other studies, such as Dicharry (2023), where the timing of spending is used as a proxy for absorptive capacity. Previous work (Incaltarau et al., 2020; Surubaru, 2017; Mendez and Bachtler, 2022) suggests that a timely absorption of EU funds correlates with the quality of local institutions regarding administrative performance and the absence of corruption. Regions that manage to spend their financial allocations within the planned timeframe have efficient administrations that are also, as we demonstrate in Section 3, most likely able to direct funding toward growth-enhancing infrastructures and incentives. From a procedural point of view, spending allocations on time makes it possible to avoid concentrating spending in the last years of an EU programming cycle when the urgency to exhaust the budget lowers the quality of spending.

We measure absorptive capacity using the dataset on regionalised Cohesion policy expenditure gathered from DG REGIO (Lo Piano et al. 2017) focusing on the 2000-2006 programming period. Our dataset combines information on regional expenditure with observable regional predetermined characteristics to feed into the ML algorithm. Features are all measured before 2000 and cover multiple domains, selected by taking the dimensions considered in the EQI index (Charron et al. 2015) as guidance and further extended. The main areas covered include demography and health, labour market conditions, youth and gender inequalities, infrastructure endowment, productivity measures with sectoral differences, investment, education and training. Information is collected at NUTS2 level data covering 27 European countries (AT, BE, BG, CY, CZ, DE, DK, EE, EL, ES, FI, FR, HU, IE, IT, LT, LU, LV, MT, NL, PL, PT, RO, SE, SI, SK, UK) and is extracted from four different data sources: Eurostat, Urban Data Platform, Urban Data Platform Plus, QOG database. The full dataset consists of about 268 regions. Collinear variables in a simple regression of absorptive status on our covariates and variables with missing values are excluded. ML algorithms are run over about 170 features.

We rely on a binary classification of absorptive capacity which is computed as the ratio between the expenditure up to 2006 over the total regional budget for the 2000-2006 programming period. We also take into account the different funding streams through which the policy is delivered (ESF, ERDF, EAFRD and CF).[3] Regions with low AC are those that spent less than 75% of the allocated budget by the last year of the programming period (corresponding to the 6th decile of the distribution of the total expenditure rate). Our sample consists of 843 region-fund observations of which 503 have a low absorptive capacity. We also test the sensitivity of our results by considering alternative thresholds of the rate of expenditure: 72% (the median) and 76% (the 7th decile). In addition, we also examine how the results vary when the absorptive capacity of the previous programming period is included in the prediction model, in order to test whether the past level of absorptive capacity helps explain the current level. Furthermore, we consider a continuous measure of expenditure speed as the target variable. Table A1 in the annex provides some descriptive statistics that highlight differences between regions with low and high absorptive capacity. We observe that low AC regions are characterized by a more prominent role of the agricultural and industrial sector in terms of employment and hours worked compared to high AC regions, while there are no significant differences in terms of GDP per capita, labor force and other sectoral characteristics. The table also shows that the low AC regions that spent more in the two-year extension window in the 2000-2006 programming period were not late spenders in the previous programming period (1994-1999), suggesting low AC persistence.

[3] Specifically, the European Social Fund (ESF) enhances employment opportunities and social inclusion; the European Regional Development Fund (ERDF) supports infrastructure, innovation, and regional development; the European Agricultural Fund for Rural Development (EAFRD) promotes rural development and sustainable agriculture; and the Cohesion Fund (CF) targets infrastructure and environmental projects in less economically developed regions.

Looking at the speed of expenditure, the difference between low and high AC regions is around 29 percentage points in 2000-2006 and was 3.8 percentage points in 1994-1999.

More formally, every region x at time t (programming period) has then an associated target binary variable AC_x^t (absorptive capacity) that takes values "1" (positive sample) if expenditure speed is lower than 75%, and value "0" (negative sample) otherwise. The prediction task is formulated as follows: based on the set of features described above $\{F_x^{t-1}\}$ for region x, find function $f(.)$ (machine learning model) that predicts absorptive capacity VH_x^t:

$$\{F_x^{t-1}\} \xrightarrow{f(.)} AC_x^t,\ t = 2006.$$

To improve prediction, the model is estimated and tuned on a training subsample and results are then validated on a testing subsample. We randomly divide the dataset (817 observations of which 488 are late spenders) as 70 per cent for training (572 observations of which 336 have low absorptive capacity) and 30 percent (245 observations of which 152 have low absorptive capacity) for out-of-sample testing set. The hyper-parameter optimization is only done on the training set using a repeated (10 times) five-fold cross-validation. Five different models are analysed: Least Absolute Shrinkage and Selection Operator (LASSO - Tibshirani, 1996), Random Forest (RF - Breiman, 2001), Neural Network (NN - Venables and Ripley, 2002), Gradient Boosted Machine (GBM - Friedman, 2001) and a standard logit model. An overview of the models employed in our paper is reported in Appendix (B) along with relevant references for unfamiliar readers. A comprehensive review of ML models can be found in Hastie et al. (2009).

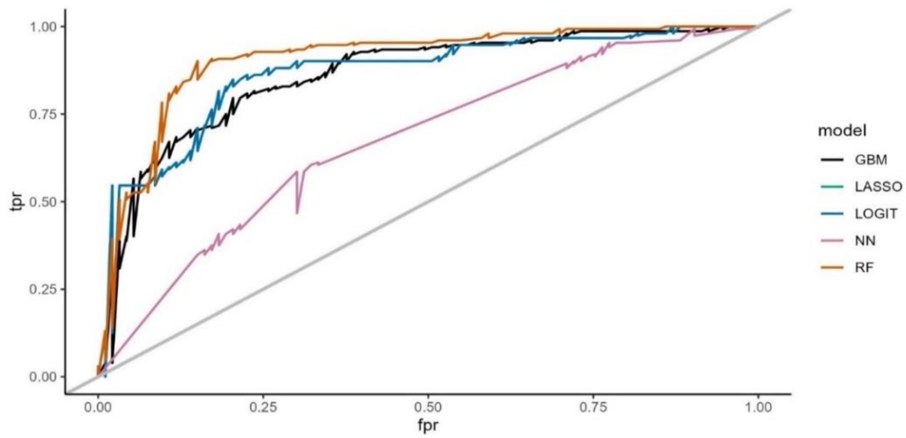
We evaluate absorptive capacity classification prediction using the ROC curve (Fawcett, 2006). DeLong's test (DeLong et al., 1988; Robin et al., 2011) determines significant differences among ROC curves from different models. In our binary classification, low absorptive capacity defines the positive class, while high AC defines the negative class. The ROC curve displays diagnostic ability by plotting the true positive rate (TPR) against the false positive rate (FPR) as the discrimination threshold varies (Antulov-Fantulin et al., 2021). TPR is the ratio of correctly identified high AC regions to the total positive samples while FPR is the ratio of low AC regions wrongly categorized as high AC to the total negative samples. An AUC of 0.5 indicates a completely unpredictable classification, while a perfect classifier achieves an AUC of 1.0. The higher the AUC, the better the prediction.

2.2 Results

This section focuses on the main results of the prediction task. Figure 1 plots the ROC curve of the five ML algorithms and a logistic regression. RF outperforms the other models and has an AUC of about 0.88. This is confirmed also by De Long's test suggesting that the difference between the ROC curve of the RF and the other models (GBM, NN and Lasso) is always statistically different from zero (Table A2).

More in detail, Table A3 shows a generalized high performance of the models in terms of prediction accuracy, as only NN (0.63) and GBM (0.79) are below 0.8. This is always higher than the no-information rate (0.62) and statistically different from the latter in all the cases except for NN. RF also exhibits higher values in terms of Sensitivity (0.85), Specificity (0.86) and balanced accuracy (0.86). A slightly better performance of RF is also confirmed with respect to the logistic regression.

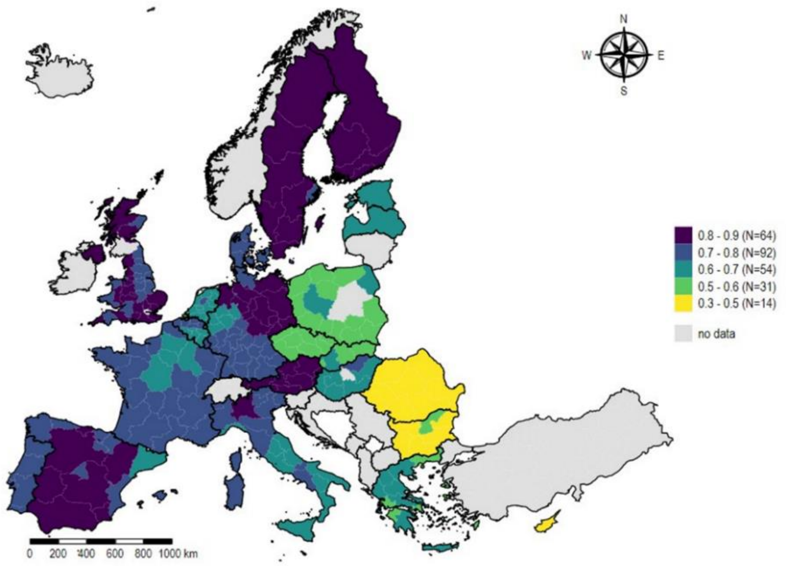
Figure 1. ROC curve



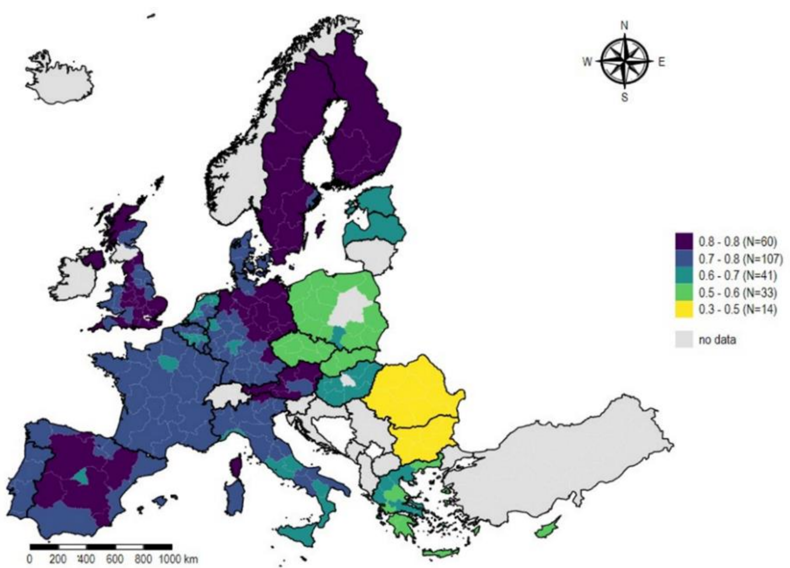
Notes: Receiver Operating Characteristics curve for four machine learning models. Models were trained on 70% of the observations and tested on the remaining 30%. Gradient boosted machine (GBM) AUC = 0.883, least absolute shrinkage and selection operator (LASSO) AUC = 0.865, logistic regression AUC = 0.865, neural network (NN) AUC = 0.562 and random forest (RF) AUC = 0.877. Resampling: cross-validated (10-fold, repeated five times).

To further validate our analysis, we also apply the ML algorithm on absorptive capacity continuously measured as expenditure speed. In this framework, the prediction exercise is no longer represented by a classification task as the target variable is continuous. Reassuringly, the accuracy of the RF model based on the proposed features is confirmed as shown in Figure 2 which compares real absorptive capacity (Panel a) with the ML predicted values (Panel b).

Figure 2. Mapping absorptive capacity (continuous target variable)



(a) real values



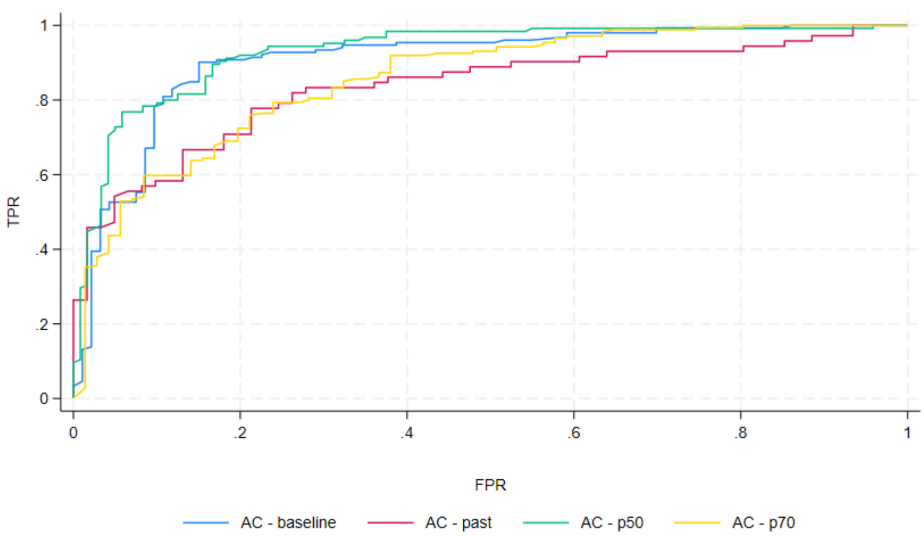
(b) Predicted values

Notes: The maps show the quintiles of the distribution of the regional spending speed of cohesion policy transfers both as real (panel a) and predicted (panel b) values. Expenditure speed is measured as the ratio of expenditure finalized by 2006 to total expenditure by the end of the programming period (including the n+2 years).

Next, we test the sensitivity of our results by considering different thresholds of expenditure speed to identify late spenders (i.e. below the median or below the 7th decile) and by including the absorptive capacity in the preceding programming period in the prediction model. Changing the threshold allows us to test if the prediction is driven by the selected cut-off points, whilst looking at past absorptive capacity helps disentangle whether the (lack of) capacity to spend is mainly explained by the "persistence" component. Throughout these settings, RF always outperforms the other models. A comparison of the ROC curves of these RF models is shown in Figure 3. Notably, results suggest that neither the selected expenditure threshold nor past expenditure ability plays a significant role in shaping current absorptive capacity. This implies that the prediction exercise highly overperforms the simple classification based on past realized expenditure speed values.

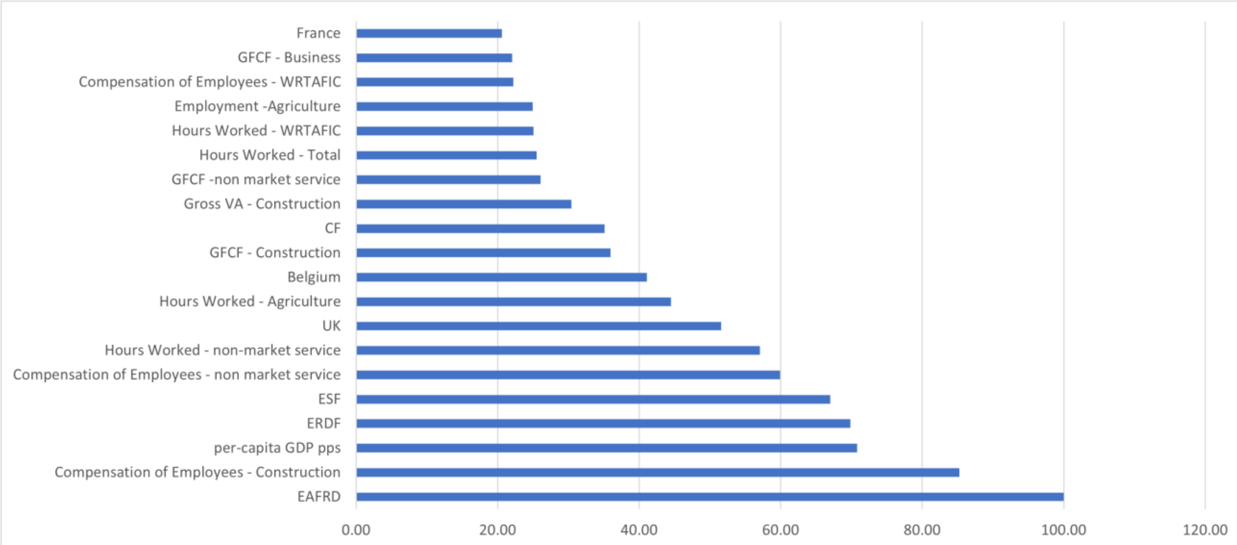
Furthermore, we dig deeper into the determinants of the regional AC exploring the relevance of each feature. Random Forest (RF) calculates importance as the mean gain of features across all trees, measured by the Gini index (Liaw, Wiener, 2002). The twenty most important features in our prediction model are plotted in Figure 4 and confirm a leading role of dimensions related to productivity (hours worked, particularly in labour-intensive sectors) and growth-related measures (per-capita GDP and sectoral gross capital formation) along with the specific characteristics of each Cohesion Policy funding stream. Albeit indirectly, this offers suggestive evidence of the relationship between the level of regional development (GDP and Value-Added measures), on the one hand, and the quality of the local human capital (hours worked and compensation of employees), on the other, and regional AC. Overall, the main determinants of local AC are strongly linked to the economic development and productivity of the regions.

Figure 3. ROC alternative specifications



Notes: Receiver Operating Characteristics curve for RF algorithms in four different prediction settings. The target variable is always the absorptive capacity (AC) of cohesion policy transfers, with different thresholds to identify the "positive" (1) values: baseline is set at the 6th decile of the distribution of the expenditure rate, p50 and p70 consider the median and the 7th decile respectively, while "past" includes the pre-existing level of absorptive capacity among the features.

Figure 4. Features importance in RF classification model.



Notes: Feature importance to predict regional absorptive capacity for the 20 most important features in random forest (RF). Random forest trained on 70% of observations and tested on the remaining 30%; Resampling: cross-validated (10-fold, repeated five times). Random Forest (RF) calculates importance as the mean gain of features across all trees, measured by the Gini index (Liaw, Wiener, 2002).

3. Impact of the EU Cohesion Policy

3.1 Methods and data

In this section, we explore whether regional AC determines a heterogeneous impact of cohesion policy on economic growth by looking at the subsequent programming period. In line with other studies (Becker et al. (2010); Pellegrini et al. (2013); Becker et al. (2018)) we exploit the discontinuity in the assignment rule of the ERDF (European Regional Development Fund) and ESF (European Social Fund) funds to apply a Regression Discontinuity Design (RDD) and estimate the Local Average Treatment Effect (LATE) of the policy around the cutoff point. The assignment mechanism of these funds includes more generous funds for regions with a per-capita GDP lower than 75% of the EU average that are classified as "Convergence Objective" (Objective-1 in the previous programming periods). This provides us with an exogenous shift in the generosity of funding across the thresholds that allows us to set up a quasi-experimental framework. Moreover, to assess the heterogeneity of the policy we stratify the sample according to the predicted absorptive capacity as suggested by Cattaneo et al. (2021). More in detail, the goal is to assess whether the treatment has a differential impact according to subgroups identified by the predicted regional absorptive capacity. To do so, we estimate the treatment effect conditional on pre-treatment characteristics (CHLATE) using a sharp RDD in a non-parametric setting (Calonico et al. 2014).

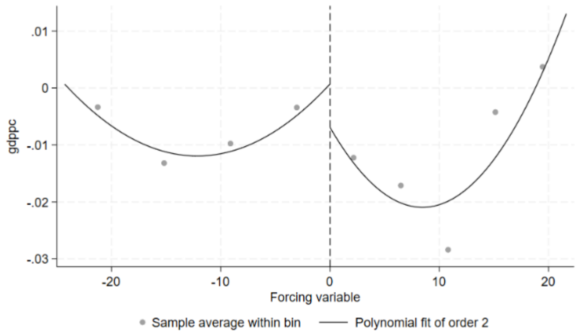
We look at the effects on a battery of economic growth outcomes: per capita GDP and three indicators on employment (total employment, employment of youth and females). Outcome variables are gathered from the Eurostat regional database. All the outcomes are expressed as the average annual difference over the period 2006-2013.

3.2 Results

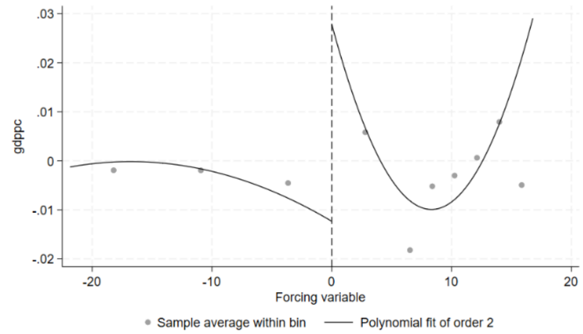
Table A4 shows the RDD estimates on these economic outcomes, distinguishing between low (late spenders) and high-capacity (early spenders) regions. All the models are estimated using robust-bias corrected standard errors (Calonico et al., 2014) with the Epanechnikov kernel, the MSE optimal bandwidth and a quadratic polynomial to have more flexibility and avoid the non-linearity issue (Angrist and Pischke, 2009). Interestingly, we find that the Cohesion policy had a positive and significant impact on some of the economic outcomes considered only for the groups of regions classified as early spenders, i.e. those having a higher absorptive capacity. Conversely, the policy had no significant effect on regions characterized by low levels of absorptive capacity and spending a large share of their funds after the closure of the programming period. More in detail, we find that the difference in per-capita GDP between 2015 and 2006 for Objective 1 regions with a predicted high absorptive capacity is higher than respective controls of about 0.038 standard deviations. A similar effect is found for female employment (0.033), while the difference is slightly higher for employment (0.067) and youth employment (0.127). Figure 5 plots the discontinuity for per-capita GDP (panel a) and employment growth (panel b), by reporting the forcing variable (75% assignment rule) on the x-axis and the outcome of interest on the y-axis. The dashed vertical line is the cut-off point which is centered around zero and separates treated regions (on the right side) from controls (on the left). The dots are averaged bins, and the thick line is the estimated polynomial. In each panel, the left-end side graph refers to the late spenders, whilst the graph on the right refers to the early spenders. Results suggest that the Cohesion policy has triggered growth in terms of GDP and employment only for early spenders (Panels a.2 and b.2).
All in all, this sheds light on the ambiguous results of the impact of EU Cohesion transfers in the economic empirical literature and highlights the importance of fostering regional absorptive capacity. Moreover, these findings suggest that money transfers might not be sufficient to trigger regional economic growth if not coupled with interventions supporting regional technical competencies and capacity to spend.

Figure 5

Panel (a) – Per-capita GDP

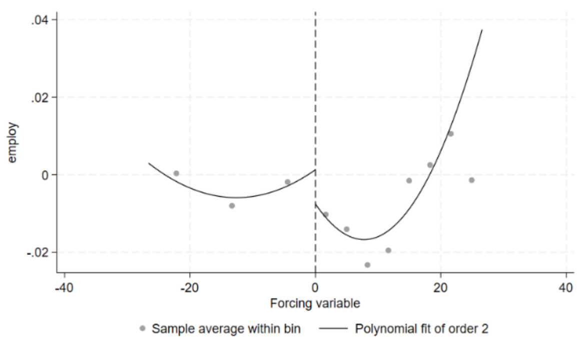


(a.1) Late spenders – low-capacity regions

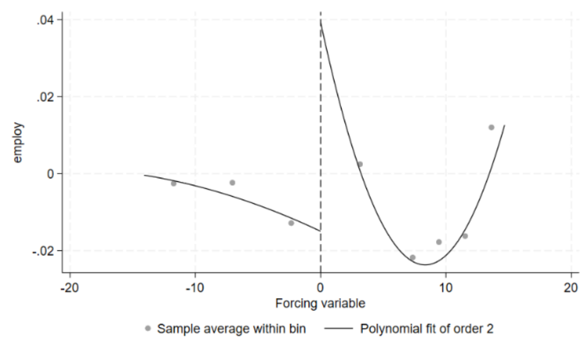


(a.2) Early spenders – high-capacity regions

Panel (b) – Employment



(a.1) Late spenders – low-capacity regions



(a.2) Early spenders high-capacity regions

Notes: The figures show the discontinuity for GDP per capita (panel a) and employment growth (panel b). The forcing variable (75% allocation rule) is on the x-axis and the outcome of interest is on the y-axis. The dashed vertical line is the cut-off point (75%) centred around zero. Treated regions (convergence objective) are on the right and controls are on the left. The points are averaged bins and the thick line is the estimated polynomial. In each panel, the graph (.1) refers to the late spenders, while the graph (.2) refers to the early spenders.

The validity of the RD Design is then tested in Appendix C. Figure C1 confirms the absence of manipulation by resorting to the McCrary test (McCrary 2008). Tables C1-C4 present the sensitivity to different model specifications: alternative kernel, alternative bandwidth, different polynomial order and fake cutoff. Reassuringly, baseline findings are largely confirmed across models.

4. Concluding remarks and Policy tuning

Economists and policymakers are increasingly interested in territorial policies, which can provide remedies to spatial market failures. However, designing effective policies remains challenging, with mixed evaluation results. This paper examines the European regional policy, which accounts for nearly one-third of the EU budget and suggests improving its effectiveness through better targeting.

We elaborate on the notion of AC, which previous literature emphasizes as a key correlate of effectiveness. Using machine learning (ML) techniques, we predict which regions will be able to manage funding accurately. Methods like Lasso, Random Forest, Neural Network, and Gradient Boosted Machine are used, with Random Forest proving most accurate based on 2000-06 data. Next, we use a Regression Discontinuity Design (RDD), showing EU funds spur growth and employment only in regions predicted with high AC.

Our empirical exercise suggests that the current EU framework needs to be revised. The current scheme seems to work well for high-AC regions. However, low-AC regions do not receive the expected benefits in terms of GDP growth and employment from EU funds. Our study allows us to identify the two types of regions at the start of the program. We suggest that for low-AC regions, improving local AC before providing funds could be an appropriate policy tuning. This could be done by granting technical assistance and/or through a process of capacity building. One possible use of our study is to focus capacity-building activities on regions that are predicted to have low effectiveness Alternatively, funds can be provided subject to additional safeguards, such as delegating expenditure management to independent agencies that have the expertise that national authorities do not have.

While revisiting the scheme will increase the effectiveness of the policy, and likely also its equity given that nowadays the less developed regions are those that receive less, we are aware that our proposal can be difficult to implement because of the difficulties related to the transparency, which is the sore point of the algorithmic decisions. The ability to communicate will be a key component of the revision of the scheme. On the bright side, our ML-based predictions, using publicly available data and off-the-shelve algorithms offer a practical tool for policymakers.

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Appendix A

Table A1. Descriptive statistics

Variable	Unit	Mean T	Sd Mean T	Mean C	Sd Mean C	Diff(T-C)	P-val Diff	N obs T	N obs C
Absorptive capacity measures									
Expenditure after the last year (2006)	million	96.87	132.04	67.83	71.68	29.04	0.092	195	65
Expenditure speed	%	67.88	9.46	78.65	3.47	-10.76	0.000	195	65
Expenditure after the last year (1999)	million	41.29	66.58	40.63	52.65	0.66	0.944	144	64
Expenditure speed (1994-1999)	%	76.31	7.58	80.10	6.48	-3.80	0.001	144	64
Other regional characteristics									
GDP	million	37,605.11	49,571.50	35,859.11	22,662.95	1,746.01	0.784	195	65
Active population	thousands	887.67	753.60	738.42	397.66	149.25	0.128	195	65
per-capita GDP in pps	thousands	17.67	7.76	18.71	5.20	-1.03	0.318	195	65
Gross Value Added - by sector									
Financial and Business	million	8,430.42	14,353.08	8,321.55	7,083.10	108.87	0.953	195	65
Industrial	million	7,020.45	8,886.70	6,849.36	4,340.34	171.10	0.882	195	65
Non-market service	million	7,043.02	8,770.94	7,153.55	4,283.64	-110.53	0.922	195	65
Total	million	33,625.52	44,765.60	32,186.86	20,416.18	1,438.66	0.803	195	65
WRTAFIC	million	8,334.73	11,934.22	6,958.48	4,931.77	1,376.25	0.367	195	65
GFCF - by sector									
Construction	million	254.80	439.23	268.69	228.92	-13.89	0.807	195	65
Financial and Business	million	2,846.29	4,306.36	3,006.65	2,266.62	-160.36	0.774	195	65
Industrial	million	1,878.49	2,334.15	1,692.56	1,226.71	185.93	0.540	195	65
Non-market service	million	1,380.34	1,767.01	1,254.46	1,010.63	125.87	0.586	195	65
Total	million	8,056.00	10,086.99	7,817.55	5,000.56	238.45	0.855	195	65
WRTAFIC	million	1,467.17	2,054.49	1,414.83	1,081.69	52.34	0.845	195	65
Construction	million	2,060.94	2,479.80	2,406.85	1,431.84	-345.91	0.287	195	65
Employment - by sector									
Agriculture	thousands	74.28	152.77	22.23	28.14	52.05	0.007	195	65
Construction	thousands	54.26	48.28	53.00	35.16	1.26	0.846	195	65
Financial and Business	thousands	96.55	135.43	89.93	70.72	6.62	0.707	195	65
Industrial	thousands	168.91	158.23	113.32	63.00	55.59	0.006	195	65
Non-market service	thousands	216.84	207.14	193.07	112.25	23.77	0.378	195	65
WRTAFIC	thousands	205.60	204.87	181.01	102.31	24.60	0.354	195	65
Hours worked by sector of activity									
Agriculture	hours	144.99	270.70	48.29	60.50	96.71	0.005	195	65
Construction	hours	106.67	95.18	107.77	62.59	-1.10	0.931	195	65
Financial and Business	hours	373.94	346.63	337.23	178.54	36.71	0.414	195	65
Industrial	hours	305.60	291.40	217.95	117.95	87.65	0.019	195	65
Non-market service	hours	377.26	362.50	302.74	166.30	74.51	0.111	195	65
Total	hours	1,426.38	1,238.41	1,104.97	576.27	321.41	0.045	195	65
WRTAFIC	hours	158.42	212.49	133.69	103.35	24.73	0.368	195	65

Variable	Unit	Mean T	Sd Mean T	Mean C	Sd Mean C	Diff(T-C)	P-val Diff	N obs T	N obs C
Compensation of employees - by sector									
Construction	million	989.94	1,142.27	1,111.14	816.93	-121.20	0.430	195	65
Financial and Business	million	2,306.38	3,858.63	2,343.70	2,258.45	-37.32	0.941	195	65
Industrial	million	3,742.50	4,791.93	3,791.24	2,379.87	-48.74	0.937	195	65
Non-market service	million	4,693.84	5,447.30	4,986.20	3,125.69	-292.35	0.682	195	65
Total	million	15,515.84	19,394.38	16,115.72	10,373.87	-599.88	0.812	195	65
WRTAFIC	million	3,637.58	5,097.96	3,729.74	2,691.55	-92.16	0.889	195	65

Notes: The table shows the differences in the mean between two groups of regions. T denotes regions with a low AC, while C denotes regions with a high AC. All variables are measured before 2000 and T and C are defined on the basis of the AC in 2000-2006.

Table A2. Models' performance

	GBM	NNET	RF	LASSO	LOGIT
Accuracy	0.788	0.633	0.857	0.829	0.829
95% CI - lower	0.731	0.569	0.807	0.775	0.775
95% CI - upper	0.837	0.693	0.898	0.874	0.874
No information rate	0.620	0.620	0.620	0.620	0.620
p-Value (Acc > NIR)	0.000	0.373	0.000	0.000	0.000
Sensitivity	0.742	0.667	0.849	0.774	0.774
Specificity	0.816	0.612	0.862	0.862	0.862
Pos pred value	0.711	0.512	0.790	0.774	0.774
Neg pred value	0.838	0.750	0.903	0.862	0.862
Prevalence	0.380	0.380	0.380	0.380	0.380
Detection rate	0.282	0.253	0.322	0.294	0.294
Detection prevalence	0.396	0.494	0.408	0.380	0.380
Balanced accuracy	0.779	0.639	0.856	0.818	0.818
The area under the ROC curve	0.833	0.562	0.877	0.865	0.865

Notes: GBM, gradient boosted machine; LASSO, least absolute shrinkage and selection operator; NN, neural network; RF, random forest; NIR, no information rate; ROC, receiver operating characteristics.

Table A3. DeLong test for ROC curves

	z	p-value
RF versus GBM	3.223	0.001
RF versus NN	7.084	0.000
RF versus LASSO	2.501	0.012

Notes: GBM, gradient boosted machine; LASSO, least absolute shrinkage and selection operator; NN, neural network; RF, random forest; ROC, receiver operating characteristics.

Table A4. Heterogeneity in Cohesion policy effectiveness according to absorptive capacity

	(1) Δ06-13 GDP	(2) Δ06-13 GDP	(3) Δ06-13 EMPL	(4) Δ06-13 EMPL	(5) Δ06-13 EMPL F	(6) Δ06-13 EMPL F	(7) Δ06-13 EMPL YOUTH	(8) Δ06-13 EMPL YOUTH
Treat	-0.007	0.038**	-0.010	0.067***	0.008	0.033**	-0.025	0.127**
	(0.012)	(0.017)	(0.014)	(0.023)	(0.023)	(0.015)	(0.028)	(0.059)
Obs	145	107	144	106	144	106	142	106
Low AC	Y		Y		Y		Y	
High AC		Y		Y		Y		Y

Notes: The Table reports the LATE estimates obtained using the bias-corrected standard errors developed by Calonico et al. (2014) in a sharp RDD framework. The cut-off point is 75% of the EU average per-capita GDP, centred on zero for convenience. Treated regions are those having a per-capita GDP lower than the 75% threshold (Convergence objective). The model adopts the Triangular kernel, the MSE-optimal bandwidth (Calonico et al., 2019) and a quadratic polynomial. In each column, the Outcome is given by the average annual difference between the respective variables in 2006 and 2015. The heterogeneity of the impact is assessed according to the absorptive capacity (AC) distinguishing between low (late spenders) and high capacity (early spenders) regions.
*** p<0.01, ** p<0.05, * p<0.1

Appendix B

Machine-Learning Models

In a typical machine learning (ML) scenario, the goal is to predict an outcome based on a set of features. This involves using a training dataset where both the outcome and features are known.

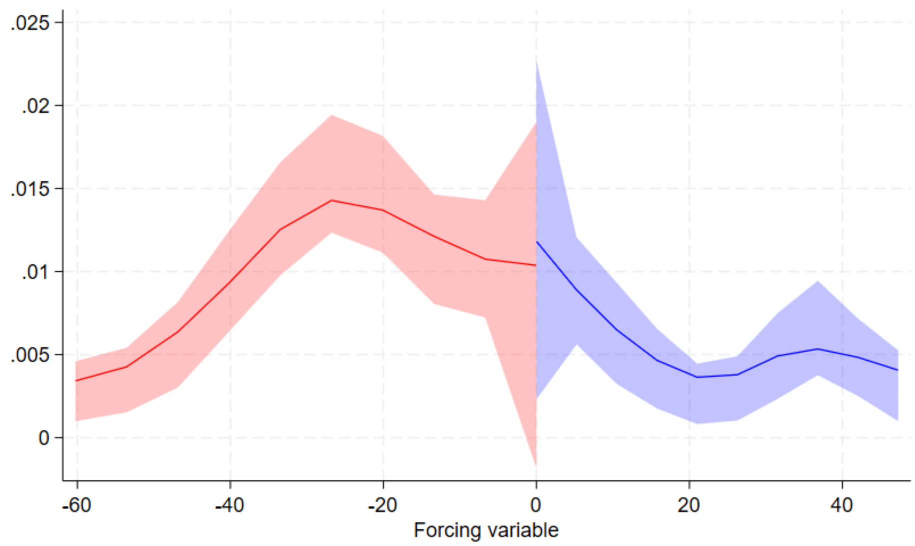
A prediction model is then constructed to forecast the outcome for new, unseen data. A reliable model can predict the outcome with high accuracy (Hastie et al. 2009).

In this study, we use four different models. LASSO is a regression method that performs feature selection and regularization using the L1 norm, which helps reduce overfitting and enhances prediction accuracy and interpretability (Tibshirani, 1996). Random Forest (RF) and Gradient Boosting Machine (GBM) are instead boosting methods that combine multiple weak learners to improve prediction performance. In particular, RF involves an ensemble of randomized decision trees, using different random subsets of features at each split (Breiman et al., 2001) while GBM corrects the pseudo-residuals of previous learners at each stage (Friedman, 2001). Finally, Neural Networks (NN) consists of interconnected input/output units, each with associated weights. During the learning phase, the network adjusts these weights to accurately predict the class label of given inputs (Venables, Ripley, 2002).

Appendix C

RDD robustness

Figure C.1 McCrary test



Notes: Estimation of the density function of the forcing variable 1988–1990) at the threshold. Shaded areas are the respective 95% confidence intervals.

Table C.1 Heterogeneity in Cohesion policy effectiveness according to absorptive capacity, alternative bandwidth selector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ06-13 GDP	Δ06-13 GDP	Δ06-13 EMPL	Δ06-13 EMPL	Δ06-13 EMPL F	Δ06-13 EMPL F	Δ06-13 YOUTH EMPL	Δ06-13 YOUTH EMPL
Treat	-0.005	0.050***	-0.007	0.094***	0.015	0.051***	-0.018	0.209***
	(0.015)	(0.019)	(0.016)	(0.028)	(0.028)	(0.020)	(0.032)	(0.079)
Obs	145	107	144	106	144	106	142	106
Low AC	Y		Y		Y		Y	
High AC		Y		Y		Y		Y
BW Type	cerrd	cerrd	cerrd	cerrd	cerrd	cerrd	cerrd	cerrd

Notes: The Table reports the LATE estimates obtained using the bias-corrected standard errors developed by Calonico et al. (2014) in a sharp RDD framework. The cut-off point is 75% of the EU average per-capita GDP, centred on zero for convenience. Treated regions are those having a per-capita GDP lower than the 75% threshold (Convergence objective). The model adopts the Triangular kernel, the CER-optimal bandwidth and a quadratic polynomial. In each column, the Outcome is given by the average annual difference between the respective variables in 2006 and 2015. The heterogeneity of the impact is assessed according to the absorptive capacity (AC) distinguishing between low (late spenders) and high capacity (early spenders) regions.
*** p<0.01, ** p<0.05, * p<0.1

Table C.2 Heterogeneity in Cohesion policy effectiveness according to absorptive capacity, alternative kernel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ06-13 GDP	Δ06-13 GDP	Δ06-13 EMPL	Δ06-13 EMPL	Δ06-13 EMPL F	Δ06-13 EMPL F	Δ06-13 EMPL YOUTH	Δ06-13 EMPL YOUTH
Treat	-0.007	0.048**	-0.010	0.125***	0.007	0.079***	-0.026	0.281***
	(0.012)	(0.019)	(0.013)	(0.036)	(0.022)	(0.027)	(0.027)	(0.104)
Obs	145	107	144	106	144	106	142	106
Low AC	Y		Y		Y		Y	
High AC		Y		Y		Y		Y
Kernel Type	Epa	Epa	Epa	Epa	Epa	Epa	Epa	Epa

Notes: The Table reports the LATE estimates obtained using the bias-corrected standard errors developed by Calonico et al. (2014) in a sharp RDD framework. The cut-off point is 75% of the EU average per-capita GDP, centred on zero for convenience. Treated regions are those having a per-capita GDP lower than the 75% threshold (Convergence objective). The model adopts the Epanechnikov kernel, the MSE-optimal bandwidth (Calonico et al., 2019) and a quadratic polynomial. In each column, the Outcome is given by the average annual difference between the respective variables in 2006 and 2015. The heterogeneity of the impact is assessed according to the absorptive capacity (AC) distinguishing between low (late spenders) and high capacity (early spenders) regions.
*** p<0.01, ** p<0.05, * p<0.1

Table C.3 Heterogeneity in Cohesion policy effectiveness according to absorptive capacity, alternative polynomial order

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ06-13 GDP	Δ06-13 GDP	Δ06-13 EMPL	Δ06-13 EMPL	Δ06-13 EMPL F	Δ06-13 EMPL F	Δ06-13 EMPL YOUTH	Δ06-13 EMPL YOUTH
Treat	-0.005	0.061***	-0.006	0.081***	0.017	0.064**	-0.021	0.158**
	(0.017)	(0.023)	(0.018)	(0.028)	(0.030)	(0.026)	(0.033)	(0.072)
Obs	145	107	144	106	144	106	142	106
Low AC	Y		Y		Y		Y	
High AC		Y		Y		Y		Y
Order Loc. Poly.	3	3	3	3	3	3	3	3

Notes: The Table reports the LATE estimates obtained using the bias-corrected standard errors developed by Calonico et al. (2014) in a sharp RDD framework. The cut-off point is 75% of the EU average per-capita GDP, centred on zero for convenience. Treated regions are those having a per-capita GDP lower than the 75% threshold (Convergence objective). The model adopts the Triangular kernel, the MSE-optimal bandwidth (Calonico et al., 2019) and a cubic polynomial. In each column, the Outcome is given by the average annual difference between the respective variables in 2006 and 2015. The heterogeneity of the impact is assessed according to the absorptive capacity (AC) distinguishing between low (late spenders) and high capacity (early spenders) regions.
*** p<0.01, ** p<0.05, * p<0.1

Table C.4 Heterogeneity in Cohesion policy effectiveness according to absorptive capacity, fake cutoff

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ06-13 GDP	Δ06-13 GDP	Δ06-13 EMPL	Δ06-13 EMPL	Δ06-13 EMPL F	Δ06-13 EMPL F	Δ06-13 EMPL YOUTH	Δ06-13 EMPL YOUTH
RD_Estimate	0.004	-0.004	0.001	0.007	0.005	-	-0.020	0.012
	(0.025)	(0.018)	(0.019)	(0.014)	(0.017)	-	(0.040)	(0.036)
Obs	145	107	144	106	144	ins. obs.	142	106
late	Y		Y		Y		Y	
early		Y		Y		Y		Y
Cut-off	10	10	10	10	10	10	10	10

Notes: The Table reports the LATE estimates obtained using the bias-corrected standard errors developed by Calonico et al. (2014) in a sharp RDD framework. The cut-off point is arbitrarily set at a value of 10 instead of zero. The model adopts the Triangular kernel, the MSE-optimal bandwidth (Calonico et al., 2019) and a quadratic polynomial. In each column, the Outcome is given by the average annual difference between the respective variables in 2006 and 2015. The heterogeneity of the impact is assessed according to the absorptive capacity (AC) distinguishing between low (late spenders) and high capacity (early spenders) regions.
*** p<0.01, ** p<0.05, * p<0.1