# Impact of European Cohesion Policy on regional growth:

# When time isn't money

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#### August 2021

#### Abstract

This paper contributes to the literature discussing the effects of the EU Funds on GDP growth by revealing the causal impact of regional absorption's speed. The analysis is conducted using a regression discontinuity design approach with heterogeneous treatment on NUTS-2 regions during the period 2000-2016. We show that a faster absorption, especially in the Mediterranean regions, is associated with worse economic outcomes of the Objective 1 treatment. The opposite holds for non-treated regions. Regarding policy implications, this study suggests that the decommitment rule should be softened, or even removed for Objective 1 regions.

Keywords: Regional economic growth; European Cohesion Policy; absorption capacity; regression discontinuity design.

JEL classification: E62, H50, R58

### 1 Introduction

Cohesion Policy is designed to foster economic homogeneity across countries and regions of the EU to make their market integration be successful. In 1989, Jacques Delors, president of the European Commission between 1985 and 1995, argued that the Cohesion Policy is meant " to give every region an opportunity to benefit from the enormous advantages the single market will bring".<sup>1</sup> For the current programming period 2014-20, they constitute the second-largest budget line after the EU's Common Agricultural Policy as they stand for almost a third of the European budget. A special scheme has been designed for NUTS-2 regions characterised by GDP per capita lower than 75% of the per capita European GDP average making them eligible for the Objective 1 treatment. Since the programming period 1989-94, this status allows some regions to benefit from markedly increased EU transfers to fasten their convergence process.

To make an efficient use of this European rent, recipient regions must use these transfers in investment projects generating additional economic growth. A high regional absorption capacity is therefore necessary to reach these policy goals. The European Commission defines absorption capacity as "the ability to use the financial resources made available [...] on the agreed actions and according to the agreed timetable.<sup>2</sup> Therefore, the absorption speed of the EU funds constitutes a policy target for the European Commission as it is considered as a signal for the absorption capacity of a recipient region. <sup>3</sup> To accelerate absorption, a portion of the budgetary commitment is even automatically decommitted by the Commission if it has not been used or if no payment application has been received by the end of the second year following that of the budgetary commitment  $(n+2 \ rule)$ . This rule has been introduced in 1999 due to a growing concern at the EU level about the poor financial performance of some EU regional development programmes. The programming period 2014-20 has been characterised by a softer rule since the decommitment procedure has been postponed 3 years after the end of the programming period  $(n+3 \ rule)$ . Observing a slowdown in the absorption speed, the Commission has proposed to return to the  $n+2 \ rule$  for the programming period 2021-27 (Bachtler et al. (2019)).

Figure 1 below indicates the share of EU payments implemented after the end of their corresponding programming period, *i.e.* the late payments, for each NUTS-2 region for the programming periods 1994-99, 2000-06 and 2007-13. It can be noticed that the European map becomes more reddish across time, indicating that late payments are an increasing phenomenon. During the 2007-13 period, a vast majority of regions have more than 50% of late payments, a share outrunning 75% in most of the English, Belgian and Portuguese regions. It is worth mentioning that only 25% of the observations of this study have a share of late payments lower than 20%, while 30% of observations outreach the 80% threshold. According to Figure 1, it appears that regions having the fastest absorption are mostly located in Sweden, Finland and Greece.

Fast absorption is helpful in the sense that it avoids decommitments of EU payments. For instance, regarding the programming period 2000-06, substantial amounts were decommitted in the Netherlands (11.1%), Luxembourg (10.8%) and Denmark (6.1%) resulting from a slow absorption (Bachtler & Ferry (2015)). However, one drawback of spending faster might be spending worse. "Some Member States are

critical of n+2 and argue that it will lead to a recurrence of problems with preparing and managing large, high-value projects, encourage a less strategic approach to project selection" (Bachtler et al. (2019), p.39).

#### [Figure 1 over here]

The novelty of this paper is to assess whether fast absorption of the EU funds constitutes a desirable policy outcome of the Cohesion Policy. In other words, should we trust absorption speed in evaluating the absorption capacity of a recipient region? Is it a suitable proxy for absorption capacity?

To study this question, this paper contributes to existing research by exploiting a new source of the conditional impact of the Cohesion Policy on regional economic growth: the absorption speed of the EU funds in recipient NUTS-2 regions. Our analysis aims to determine whether the delays in EU payments may generate a heterogeneity in the Objective 1 treatment's effect on economic growth of recipient regions. In other words, we intend to determine whether the magnitude of the impact of the EU funds in lagging regions is fully determined by their pace of spending.

The estimation methodology of this paper is based on Becker et al. (2013) which exploits the discrete jump in the probability of EU transfer receipt at the 75% threshold to conduct a fuzzy regression discontinuity design (RDD) with heterogeneous local average treatment effect (HLATE). While Becker et al. (2013) estimates the impact of the Objective 1 treatment based on regional governance quality and human capital level, we are focused on the regional absorption rate of the EU funds. To increase the reliability of our estimates, we consider real EU payments from the database of Lo Piano et al. (2017) that follows the dates in which expenditures took place on the ground. This is not the case of commitments, usually employed in the literature studying the economic effectiveness of the Cohesion Policy (see *e.g.*,Becker et al. (2010, 2013), Pellegrini et al. (2013), Rodriguez-Pose & Garcilazo (2015), Gagliardi & Percoco (2017), Percoco (2017), Becker et al. (2018)).

Our paper shows that a faster absorption of the EU funds reduces the effectiveness of the Cohesion Policy in Objective 1 regions, or the ability of the EU funds to stimulate economic growth. In other words, faster the EU funds are absorbed in Objective 1 regions, lower is the impact on economic growth. This result reveals the tension between *spending good* and *spending fast* in the European lagging regions as they are generally characterised by a lower absorption capacity.

This illustrates the fact that fast absorption might be the outcome of a strategic behaviour of recipient regions or governments to send a signal of good management to the European authorities (Huliaras & Petropoulos (2016), Aivazidou et al. (2020)). A quantile regression analysis suggests that this result is especially valid in regions with the lowest economic growth performances, the latter being mostly located in the Mediterranean Europe. A second result is that slow absorption has a negative impact on economic growth in non-treated regions. As they are wealthier, they receive significantly less EU transfers and are generally characterised by a higher absorption capacity (Becker et al. (2012)), which gives little room to conduct the strategic behaviours aimed at increasing absorption rates. Therefore, in non-treated regions, slow absorption would rather be the outcome of a lower management quality (Dudek (2005), Milio (2007), Tosun (2014), Surubaru (2017), Incaltarau et al. (2020)). These results are robust

to different specifications, sample compositions and outcome variables.

The interpretation pertaining to policy implications is easily implementable by policymakers as we propose to remove the *one-size fits all* logic of the decommitment rule. We suggest to introduce a placebased approach dimension considering the lower absorption capacity of Objective 1 regions. Therefore, a differentiated decommitment rule between Objective 1 and wealthier regions, or even a suspension of the rule for the Objective 1 regions, could help to mitigate the use of strategies detrimental to the effectiveness of the Cohesion Policy.

The remainder of this paper is organised as follows: Section 2 provides a related literature review. Section 3 deals with the methodology and data used to conduct our analysis. Section 4 provides the estimation results, the robustness tests alongside with the discussion. We conclude in Section 5.

## 2 Related literature

Among the large literature dealing with the Cohesion Policy, the local quality of governments has unanimously been investigated as a promoting factor of the conditional impact of the EU funds on regional economic growth resulting from a higher absorption capacity (see *e.g.*,Ederveen et al. (2006), Becker et al. (2013), Mendez et al. (2013), Rodriguez-Pose & Garcilazo (2015), Dall'Erba & Fang (2017)). For instance, Dall'Erba & Fang (2017) offers a meta-regression analysis of the impact of EU funds on regional growth of recipient regions based on 323 estimates in 17 econometric studies. Human capital and quality of institutions are identified as "characteristics of the recipient regions that condition the effectiveness of the funds (Dall'Erba & Fang (2017), p.10).

Some recent studies highlight that fast absorption is a signal for high absorption capacity resulting from a sound institutional environment (Dudek (2005), Milio (2007), Tosun (2014), Surubaru (2017), Incaltarau et al. (2020)).Tosun (2014) explores the determinants of the absorption pace with regard to the European Regional Development Fund's (ERDF) 2000–06 programming period and finds that Member States' government effectiveness is positively associated with the speed of absorption of the ERDF. As well, Surubaru (2017) associates faster absorption to better institutions and stronger administrative capacity. This comparative study mentions that in the case of Bulgaria, the result of the favourable political and institutional environments has been a higher progression of the absorption speed than the Romanian one for the period 2007-13. A similar study conducted by Incaltarau et al. (2020) concludes on the promoting role of government effectiveness on national absorption rate.

However, the view that fast absorption results from high absorption capacity is not unanimously acknowledged (ECA (2004), Polverari et al. (2007), CSIL (2010), Huliaras & Petropoulos (2016), Aivazidou et al. (2020)). Notably, Huliaras & Petropoulos (2016) provides a case study on Greece for the programming period 2007-13. The authors highlight the weaknesses of the administrative capacity and the bad institutional environment of authorities in charge of the implementation of the Cohesion Policy. As a result, the observed fast absorption has been more the result of *easy-to-spend solutions* than a good use of the EU funds resulting from a high absorption capacity. Indeed, "In 2010, one of the top priorities of the newly elected government was not to lose 'a single euro' of the National Strategic Reference Framework 2007–2013 money" (p.8, Huliaras & Petropoulos (2016)). Similarly, Aivazidou et al. (2020) concludes that low-performance of the EU funds in the Italian regions for the programming period 2007-13 can be held accountable for the strategies aiming at increasing absorption percentages instead of fostering administrative capacity.

Regarding the decommitment rule specifically, it has been effective to fasten absorption (Bachtler & Ferry (2015), but it led the authorities in charge of the implementation of the Cohesion Policy to focus on the pace of spending rather than the quality of interventions (Polverari et al. (2007); CSIL (2010)). Moreover, this rule had a detrimental impact on the ability of the Cohesion Policy to adapt to specific regional and national contexts (EC (2011)). It could be mentioned as well that the decommitment rule put a strong pressure on local administrative resources as 50% of payments are submitted between September and December (ECA (2004)). To sum up, the faster absorption induced by the n+2 rule might have been detrimental to the conduct of the Cohesion Policy and its ability to foster regional economic growth. Therefore, our study provides insights whether fast absorption has a fostering or detrimental impact on the ability of Objective 1 treatment to stimulate growth at the regional level.

Regarding the estimation approach, Becker et al. (2010) is the first study to adopt a RDD design to exploit the existence of a threshold in the attribution of the treatment status (set as 75% of the EU per capita GDP in purchasing power parity). An extended use of the RDD is then proposed in Becker et al. (2013) where heterogeneous local effects are estimated. The analysis based on heterogeneous local average treatment effect (HLATE) showed that the degree of absorptive capacity is important in explaining differences in outcomes. This approach has then been followed by numerous studies to reveal different sources of heterogeneity on the impact of the EU funds on regional growth: Gagliardi & Percoco (2017) provides evidence that the initial distribution of land matters since rural areas closed to city centres are those where the impact of EU funds is the strongest. For example, Percoco (2017) finds that that the size of the regional service sector is detrimental to the impact of the EU funds on regional growth. Becker et al. (2018) explores heterogeneity across recipient regions in terms of their exposure to the last European financial and economic crisis and reveals that in spite of a positive impact, the effects of the European transfers are weaker in countries that have been hit harder by the crisis.

The next section presents the methodology and data employed in our analysis.

## 3 Methodology and Data

#### 3.1 Regression Discontinuity Design Estimation

In this study, we focus on the potential heterogeneity of treatment effect according to the share of late payments  $a_{i,\rho}$  which is defined as:

$$a_{i,\rho} = \frac{e u_{i,\rho-1}{}^{late}}{e u_{i,\rho-1}}$$
(1)

where  $eu_{i,\rho-1}^{late}$  denotes the payments of the last programming period  $\rho - 1$  made for a region *i* after the end of this corresponding programming period. We consider the programming periods 1994-99, 2000-06 and 2007-13. <sup>4</sup>  $eu_{i,\rho-1}$  denotes the total allocation provided to region *i* for the associated programming period  $\rho - 1$ . To sum up, late payments can be defined as the payments of programming period  $\rho$  -1 made in programming period  $\rho$ . Finally,  $a_{i,\rho}$  is bounded to [0;1].

We recall that the main contribution of this study is to analyse whether  $a_{i,\rho}$ , can be considered as a suitable proxy for regional absorption capacity by evaluating its impact on the effectiveness of the Objective 1 treatment. To answer this question, we make the hypothesis that  $a_{i,\rho-1}$  is associated with the programming period  $\rho$ . More precisely, the share of late payments of period 1994-99 is associated with 2000-06, the one of 2000-06 is associated with 2007-13, and the one of 2007-13 is associated with 2014-20. The motivations behind this assumption are threefold: (i) Operational programmes, or the detailed plans in which the Member States set out how money from the EU funds will be spent during the programming period  $\rho$ , are built in the final years of the programming period  $\rho - 1$ ; (ii) The way how the EU funds are managed in the first years of  $\rho$  might be crucially determined by the absorption capacity inherited from the period  $\rho - 1$ ; (iii) Regarding the empirical strategy, it has the advantage to avoid potential endogeneity of the interaction variable.

To conduct the analysis, we adopt a Heterogeneous Local Average Treatment (HLATE) estimation where the absorption rate may amplify or reduce the treatment effect. We rely on a Regression Discontinuity Design (RDD) in line with recent studies (see *e.g.*, Becker et al. (2013); Gagliardi & Percoco (2017); Percoco (2017); Becker et al. (2018); Cerqua & Pellegrini (2018)). RDD is based on the principle that there is an exogenous eligibility rule built on an observable variable, called the forcing variable. In this study, this is the relative GDP per capita of one NUTS-2 region expressed in purchase power parity (PPS) regarding the European average. For the programming period 2000-06, the eligibility status is determined on the basis of years 1994-96 (1997-99 for countries that have joined the EU in 2004), years 2000-02 for the programming period 2007-13 and years 2007-09 for the programming period 2014-20.<sup>5</sup>

The treatment is a binary Objective 1 indicator for a NUTS-2 region *i*. We recall that Objective 1 status leads to increased transfers aiming at reducing the gap in per capita GDP between non-treated and treated regions. One key feature is that the treatment rule is not perfectly respected. Indeed, in reality, there are some exceptions from the treatment rule due to several reasons. We could mention that the sparsely populated regions in Austria, Finland and Sweden are eligible for funds despite being above the relevant threshold of 75%. Another group comprises the outermost regions of France, Portugal and Spain, where the Canary Islands are above the 75% threshold. Finally, the last exception is the phasing-out status, *i.e.* NUTS-2 regions that were granted Objective 1 transfers in 1994-99 with a GDP higher than the 75% threshold for the period 2000-06. In a nutshell, due to the imperfect compliance of the eligibility rule, we must implement a *fuzzy* RDD design. As indicated by Imbens & Lemieux (2008), applying ordinary least squares (OLS) would lead to biased estimates because of the fuzziness of the treatment. Therefore, a two-stage least squares (2SLS) where the actual treatment is instrumented by the eligibility rule should be implemented to provide reliable estimates. We highly rely on follow Becker et al. (2013) for the entire econometric strategy.

The second stage of the 2SLS under fuzzy with a HLATE identification where the interaction variable is

the share of late EU payments is given by:

$$y_{i,\rho} = \alpha_2 + \tau \hat{t_{i,\rho}} + \zeta_{0n} (1 - \hat{t}_{i,\rho}) \tilde{x}_{i,\rho} + \eta_{0q} (1 - \hat{t}_{i,\rho}) a_{i,\rho} + \zeta_{1n} \hat{t}_{i,\rho} \tilde{x}_{i,\rho} + \eta_{1q} \hat{t}_{i,\rho} a_{i,\rho} + \theta_k \sum_{k}^{K} k_{i,\rho} + \mu_{i,\rho}$$
(2)

where  $y_{i,\rho}$  represents the GDP per capita growth of region *i* averaged for the programming period  $\rho$ ,  $\alpha_2$  is a constant and  $\mu_{i,\rho}$  is the error term.  $\tilde{x}_{i,\rho}$  is the deviation from the 75% threshold while  $a_{i,\rho}$  and  $\sum_{k}^{K} k_{i,\rho}$ , a set of *K* control variables, are expressed as the deviation from their sample mean.  $\tau$  denotes the coefficient directly associated with the fitted value of the treatment  $t_{i,\rho}$ .  $a_{i,\rho}$  is associated to coefficients  $\zeta_{1,n}$  and  $\eta_{1,q}$  when the treatment is switched-on  $(t_{i,\rho} = 1)$ .  $\zeta_{0,n}$  and  $\mu_{0,q}$  are the same coefficients when the treatment is switched-off.

Regarding the first stage regression, we use the eligibility rule that is represented through a binary variable taking the value of 1 if the NUTS-2 region has a GDP per capita below 75% of the EU average, and 0 otherwise. A linear probability model is implemented, the first stage regression is given by:

$$t_{i,\rho} = \alpha_1 + \sigma r_{i,\rho} + \beta_{0n} (1 - r_{i,\rho}) \tilde{x}_{i,\rho} + \gamma_{0q} (1 - r_{i,\rho}) a_{i,\rho} + \delta r_i + \beta_{1n} r_{i,\rho} \tilde{x}_{i,\rho} + \gamma_{1q} r_{i,\rho} a_{i,\rho} + \epsilon_{i,\rho}$$
(3)

where  $t_{i,\rho}$  represents the instrumented variable that is the treatment status of region *i* for the programming period  $\rho$ ,  $\alpha_1$  is a constant and  $\epsilon_{i,\rho}$  is the error term of the first-stage estimation. Eligibility rule for treatment in programming period  $\rho$ ,  $r_{i,\rho}$ , is determined according to the 75% threshold for region *i* that is eligible for treatment:  $r_{i,\rho} = 1$  when the forcing variable is lower or equal to 75%,  $r_{i,\rho} = 0$  in the opposite case.  $\tilde{x}_{i,\rho,T}$  is the forcing variable normalised around the 75% threshold.  $a_{i,\rho,T}$ , the interaction variable, normalised around its mean value, is associated to coefficients  $\zeta_{1,n}$  and  $\eta_{1,q}$  when there is eligibility for the treatment ( $r_{i,\rho} = 1$ ).  $\zeta_{0,n}$  and  $\mu_{0,q}$  are the same coefficients when  $r_{i,\rho} = 0$ , or when a region is not eligible for Objective 1 treatment.

The following subsection describes the data used in the analysis and their descriptive statistics.

#### **3.2** Data and descriptive statistics

We collected most of the data from Eurostat Regional Statistics. They have been completed with data from Cambridge Econometrics. The information about Objective 1 status and eligibility and about expenditures come from the European Commission. We provide all data sources in Table A1 . Our sample covers a panel data set of the the EU's NUTS-2 regions for the period 2000-16. We do not include Bulgaria, Romania, and Croatia for reasons of data availability. The resulting number of NUTS-2 regions is 244. We used the NUTS2-2013 classification employed by EC (2019) which provides the input data used to build the following index. Regarding the time dimension of the dataset, data employed in the analysis are averaged for each programming period: 2000-06 and 2007-13. Regarding the programming period 2014-20, the latest available year is 2016, so the data correspond to averages of period 2014-16.<sup>6</sup> Such a transformation is implemented because the treatment variable is determined for each programming period  $\rho$ .

It should be mentioned that only actual received payments have been considered in this study, and

not commitments as most of studies of the literature (see *e.g.*, Becker et al. (2010, 2012, 2013), Pellegrini et al. (2013), Tosun (2014), Rodriguez-Pose & Garcilazo (2015), Gagliardi & Percoco (2017), Surubaru (2017), Becker et al. (2018), Cerqua & Pellegrini (2018), Incaltarau et al. (2020)). As Lo Piano et al. (2017) declares, this dataset has the advantage to follow the dates in which expenditures took place on the ground. This is not the case of commitments, which" may negatively affect the analytic work subsequently done by the experts to carry out policy assessments or to run counterfactual impact evaluations estimating the effects of the varying intensities of the EU funds on regional growth variables. The misalignment between COM reimbursement cycle and date of the interventions on the ground (beneficiaries' expenditures) may represent a disturbance acting either as a noise or as a bias." (Lo Piano et al. (2017), p.6). Hence, we consider this modelled annual expenditure as our actual EU funds expenditure variable to increase the reliability of our estimates.

As control variables, we include *population density* as the European authorities consider that a low population density is a structural handicap to achieve economic growth. We also use both the *share of the manufacturing sector and the share of financial and business services in regional gross added value* (GVA). Moreover, we consider the *share of the active population* and the *unemployment rate* to have a proxy for the size of the labour force, and the share of the active population having achieved tertiary education as a proxy for *human capital*. Finally, to control for the effects of the asymmetric shocks from the Great Recession and the following Euro Crisis, we consider the difference between the national 10 years government-bond yield spreads (GBYS) of a region with the national German one. The rationale behind this choice of variable is that Germany is legitimate to be the benchmark economy thanks to its very favourable market conditions in issuing public debt, especially since the last decade (Debrun et al. (2019)).

Table 1 displays summary statistics for key variables of interest averaged and pooled over the programming periods 2000-06, 2007-13 and 2014-16. The outcome variable, *GDP per capita growth* is calculated as the difference between the logged-GDP per capita and its lagged value. The forcing variable, *relative GDP per capita*, is then displayed as a deviation from the 75% threshold of the EU average by the time of decision of the European Commission. The interaction variable is expressed in terms of deviation regarding the pooled sample mean value, and so are the above mentioned control variables. Regarding the interaction variable, it appears that the mean is relatively similar between regions below and above the 75% threshold, although one subsample is more than twice bigger.

#### [Table 1 over here]

#### 3.3 Validity of RDD setup and estimates of HLATE

This subsection will verify and document graphically the most important assumptions related to the RDD setup. Following Becker et al. (2018), variables are grouped and averaged in equally sized bins of 2 percentage points in width to the left and the right of the threshold level.

Identification of a causal effect of Objective 1 treatment on growth by means of RDD requires that there is a discontinuity at the threshold, which is obvious in Figure 2. The jump of the outcome variable at the threshold amounts to about 0.4 percentage point.<sup>7</sup> This result strengthens the usefulness of the RDD in apprehending the question of the impact of the EU funds on regional GDP growth.

Secondly, Figure 3 displays the density distribution of GDP per capita expressed using pooled averaged observations of programming periods 2000-06, 2007-13 and years 2014-16. The RDD setup would not be valid if a spike before the 75% threshold would have been observed as it would invalidate the exogeneity of the Objective 1 treatment. This is not suggested by Figure 3 since the density peak can be observed around a level of 90%.

Then, Figure A1 plots the interaction variable against the forcing variable. There is no indication of a jump at the 75% threshold, which ensures the validity of the RDD estimates. A similar pattern is observed for the control variables used in the analysis in Figure A3.

Finally, Figure A2 illustrates graphically how the probability of Objective 1 treatment relates to regionspecific per capita GDP relative to the European average prior to each programming period (forcing variable). While a probability jump is visible at the 75% threshold, the fuzziness of the RDD design is revealed as some regions having a relative GDP per capita higher than 75% of the European at the time of the European Commission's decision are treated, and *vice versa*.

[Figure 2 over here]

[Figure 3 over here]

### 4 Results and discussion

#### 4.1 Estimation results

In this subsection, we present main results from performed analysis regarding regional GDP per capital growth and the share of late EU payments. In general, our results support the view that the later the payments are made *i.e.* slower the absorption of the EU funds is, the higher is the effectiveness of the Cohesion Policy in Objective 1 regions.

Table 2 reports estimates of the local average treatment effect (LATE) of Objective 1 status on regional economic growth. These simple RDD regressions stand for the average effect of the Objective 1 treatment on regional growth. The LATE is estimated in two different samples: averaged observations of regions having a share of late payments below (column (1)) and above (column (2)) the sample average. The sample size is restricted to increase the reliability of the RDD estimates: we propose a subsample including regions with a relative GDP per capita 25% higher and lower than the European average at the time of decision by the European Commission, *i.e.* between 50% and 100%. Indeed, the RDD approach is based on observations that are close to this threshold since they are likely to be very similar to each others with respect to observed and unobserved characteristics, except for the outcome variable. Therefore, the mean difference in the outcomes can be attributed to the treatment effect. This average treatment effect (ATE) sacrifices external validity by focusing only on observations close to the cut-off point, that is the 75% level of the average European regional GDP per capita. Finally, we include estimates of panel fixed-effects to capture all the unobserved factors related to each NUTS-2 regions.

As it can be observed, the Objective 1 treatment has a systematic positive and significant effect for regions characterised by a share of late EU payments higher than the sample average. However, the same cannot be said for the fast spending regions as the LATE is positive and significant only for the RDD estimate including the entire sample, which could be considered as the less reliable estimate because of the between regions comparability issue. Otherwise, the Objective 1 treatment does not have any significant effect on regional per capita GDP growth. Consequently, the estimates displayed in Table 2 might reveal an heterogeneous impact of the Objective 1 treatment according to the EU transfers' absorption pace. This legitimates to study the heterogeneous local average treatment effect (HLATE) of the Objective 1 treatment based on the share of late EU payments.

#### [Table 2 over here]

The estimation results for the heterogeneous effects (HLATE) are displayed in Table 3. To increase the reliability of RDD estimates as much as possible, we restrict our sample to 12.5% around the eligibility threshold, *i.e.* NUTS-2 regions having a GDP per capita from 62.5% to 87.5% of the European average (columns (1)-(2)). One drawback of this procedure is the sharp reduction of sample size since the number of observations falls to 219. Columns (3) and (4) include regions with a relative GDP per capita between 50% and 100% of the European average, which allow us to nearly double the sample size to 394 observations. Columns (5) and (6) include the entire sample as only regional fixed effects are included with the use of panel fixed-effects. It is not worth mentioning to indicate that some non-linearity is introduced with the squared term of the share of late payments in columns (2), (4) and (6). The analysis shows that weak instruments and endogeneity tests are generally verified. For sake of brevity, we report only second-stage estimates.

The first striking result is that a faster absorption of the EU funds reduces the effectiveness of the Cohesion Policy in Objective 1 regions, or the ability of the EU funds to stimulate economic growth. Indeed, in all specifications, the coefficient on the term of interaction between the share of late payments and the treatment exhibits a positive sign. The introduction of a quadratic interaction term even reinforces this result. In all specifications, we obtain  $\frac{\partial y_{i,\rho}}{\partial a_{i,\rho}} > 0$  for Objective 1 regions which indicates that the net effect of an increase in the share of late payments is beneficial to regional growth. This result validates that fast absorption might be the outcome of a strategic behaviour of recipient regions or governments to send a signal of good management to the European authorities (Huliaras & Petropoulos (2016); Aivazidou et al. (2020)). This finding gives ground to the conflict between spending fast and spending good in lagging regions as they are generally characterised by a lower absorption capacity (Becker et al. (2013)). In other words, local managing authorities may encounter more difficulties to spend a European subsidy efficiently for a given time period compared to a wealthy region.

A second result is that slow absorption has a negative impact on economic growth in regions having a relative GDP per capita higher than 75% of the European average. Indeed, as they do not benefit from the Objective 1 treatment, we find that  $\frac{\partial y_{i,\rho}}{\partial a_{i,\rho}} < 0$ . As these regions are wealthier than the Objective 1 regions,

they receive significantly less EU transfers and are generally characterised by a higher absorption capacity (Becker et al. (2012)), which gives little room to conduct the strategic behaviours aimed at increasing absorption rates. Therefore, in non-treated regions, slow absorption would rather be the outcome of a lower management quality (Dudek (2005), Milio (2007), Tosun (2014), Surubaru (2017), Incaltarau et al. (2020)).

A third result is the treatment does not have any robust direct impact on regional economic growth, making its impact purely conditional. Indeed, in all regressions, the magnitude of the impact of the EU funds in lagging regions is fully determined by their pace of spending. Therefore, the Objective 1 treatment does not promote economic growth *per se*. This finding is in line with a large majority of the literature underlining that the effectiveness of the Cohesion Policy mostly relies on regional governance quality and human capital level (see *e.g.*, Cappelen et al. (2003), Becker et al. (2013), Rodriguez-Pose & Garcilazo (2015), Becker et al. (2018)).

Regarding control variables, half of them are characterised by insignificant effects. The remaining ones are associated with the expected significant effects: (i) it could be noticed that the proxy for human capital, *i.e.* tertiary education achievement, is associated to a positive and significant impact on per capita GDP growth in most of specifications; (ii) a similar outcome appears for the share of the manufacturing sector in regional gross added value, indicating that the industrial sector is a powerful growth driver (Baumol (2001)); (iii) it is worth mentioning the robust negative significant impact of the GBYS on per capita GDP growth. This feature reveals that the the inclusion of this control variable is relevant to capture the shocks inherited from the Great Recession and the following Euro Crisis.

#### [Table 3 over here]

To give strength to these results, we conduct additional regressions using a different outcome variable, the growth of per capita regional investment, as the initial aim of the Cohesion Policy is to stimulate public and private investment to foster regional GDP growth. The structure of Table A2 is the same as Table 3. The estimation results, available in the appendix, are qualitatively similar.

Following the methodology of Becker et al. (2013), we implement non-parametric regressions based on local linear estimator with bootstrapped estimations (500 times). The optimal bandwidth is selected using the improved AIC of Hurvich et al. (1998). The non-parametric estimates are derived from a specification with both linear GDP per capita and share of late payments. The variability of the HLATE function according to the share of late payments is displayed in Figure 4. It can be observed that an increase in the share of late payments has a positive effect on the effect of the treatment on regional per capita GDP growth since the HLATE is an increasing function. It should be noticed that the non-parametric HLATE function is steeper. Moreover, while the HLATE estimated with the RDD estimator is always positive, the non-parametric estimated HLATE is negative for all late payments below the sample mean value. Figure A4 in the appendix displays similar estimates where the dependent variable is per capita investment growth. The estimation results are qualitatively similar.

### [Figure 4 over here]

Given the nature of the projects financed by the Objective 1 financial transfers (*e.g.*, transport infrastructure or research projects), our previous estimation results may be affected by spatial autocorrelation. This is confirmed by Moran's I test over that is always below 0.2 but systematically significant, indicating modest spatial autocorrelation. <sup>8</sup> To tackle this issue, spatial auto-regressive fixed effects estimates are conducted. A weighting contiguity matrix based on the 244 NUTS-2 regions of our sample is created where first and second order neighbours have the same weight. The estimation results are reported in Table 4. Whilst remaining robust, it can be noticed that the significance of late payments is reduced to the 10% level where per capita GDP growth is the dependent variable. It can still be observed that: (i) an increase in the share of late payments in Objective 1 regions is not detrimental to economic growth; (ii) the opposite holds in non-treated regions (iii) the effect of the Objective 1 treatment is mostly conditional.

#### [Table 4 over here]

The next subsection deals with additional regressions to increase the precision of our estimates. First, quantile regressions are implemented to investigate whether the treatment effects are homogeneous across per capita GDP growth levels. Moreover, following the conclusions of Becker et al. (2012), we investigate whether the intensity of the European transfers is relevant in determining their capacity to stimulate economic growth in recipient regions.

#### 4.2 Additional results

The quantile regressions estimates are displayed in Table A3 in the appendix. It can be observed that the absorption speed appears to be relevant only in regions exhibiting the lowest economic growth patterns, which are mostly located in Southern Europe. Considering that most of the Objective 1 regions are located in the Mediterranean and the Central Eastern European (CEE) countries, 47% of the regions in the lowest 25% quantile, in terms of economic growth, belongs to the Mediterranean Europe and 5% to the CEE countries. On the contrary, if we consider the upper 25% quantile, where the absorption speed appears to be irrelevant, the CEE countries stand for 31% of the sample and this share falls to 30% for the Mediterranean ones.

Then, we conduct a heterogeneity analysis based on the conclusions of Becker et al. (2012). This study states that high EU transfers GDP intensity may not be appropriate for regions characterised by a low absorptive capacity. Indeed, "regions with a transfer intensity of more than 1.3% of GDP could give up EU transfers without experiencing a significant drop in their average annual per-capita income growth rate" (Becker et al. (2012), p. 664). To ensure the best comparability of our estimates, we divide our total sample in two equal sub-samples: (i) regions with a EU funds intensity below the median value (0.15% if per capita GDP), (ii) regions with a EU funds intensity above the median value. The rationale behind this approach is to test whether the fast spenders endowed with substantial European transfers, generally associated with a low absorption capacity, make a good use of these resources. The estimation results in Table A4 indicate that the outcomes of the low intensity regions are similar to those associated to non-treated regions, and *vice versa* with high intensity and Objective 1 regions. Indeed, in regions

with less transfers, the share of late payments is detrimental to economic growth and can be interpreted as a signal for a lower absorption capacity. On the contrary, in regions receiving a lot of EU transfers, the share of late payments is not a signal suitable for regional absorption capacity. The next subsection discusses the estimation results.

#### 4.3 General discussion

Firstly, our results indicate that fast absorption in the Objective 1 regions is not a desirable policy outcome since a faster absorption is significantly associated with a lower effectiveness of the Cohesion Policy in terms of stimulation of economic growth. These results especially corroborate the findings of Huliaras & Petropoulos (2016). In details, the latter focuses on Greece, especially during the 2007-13 period, and reveals that every time a programming period end was approaching, the political authorities targeted easy to spend solutions, such as unconditional direct subsidies to small and medium-sized enterprises or the construction of parking facilities to keep authorities satisfied and exhibit the fact that all the European money has been spent on time. Moreover, the conclusions of Huliaras & Petropoulos (2016) particularly corroborate our estimation results as we have shown that fast absorption is the most detrimental in Objective 1 regions with poor growth performances (see Table A3), where the Greek regions stand for 18% of our observations. Regarding the n+2 rule in particular, our results are in line with the literature pointing out that this rule resulted in an increased focus on the pace of spending rather than the quality of the investment projects (CSIL (2010)), especially in regions with limited administrative resources (ECA (2004)), as the Objective 1 regions. While a strand of the literature concludes on a positive association between regional administrative capacity and the speed of the implementation of the Cohesion in Spain (Dudek (2005)), Italy (Milio (2007)), Romania and Bulgaria (Tosun (2014)), we posit that absorption pace is failing signal for absorption capacity. Indeed, it does not capture local strategies implemented to fasten absorption at the cost of lower economic effectiveness. For instance, the use of retrospective projects consists on funding projects which have incurred expenditure, or are completed before the EU co-financing has been formally applied, *i.e.* they are financed retrospectively. As these projects are often selected, initiated or carried out without having been expressly linked to a programme's objectives or to specific legal requirements linked to EU assistance, they exhibit a significant risk of low economic effectiveness (ECA (2018)). Aivazidou et al. (2020) mentions as well the reduction of regional share of contribution as a strategy to increase absorption rates. This study proposes then an alternative measure of absorption, the net absorption rate of total funding based on the initial total commitments (net ITAR) to alleviate the bias of this strategy on absorption rates.

Our results give ground to the tension between *spending fast* and *spending good*. The origins of this trade-off have been somewhat theorised by the literature dealing with the political economy of the EU funds (see *e.g.*, Dellmuth (2011), Charron (2016)). This literature underlines the existence of two objectives: (i) a full and fast absorption of the European funds on one side, (ii) achieving regional cohesion by aiding lagging regions on the other side. During the implementation of the Cohesion Policy, the European Commission and the Member States can be considered as Principals, and recipient regions as Agents. The policy goal of the European Commission is to maximise the absorption rates of recipient regions to send a

signal that the EU funds are fully used, so as to provide incentives to the Member States to increase their financial contribution for the next programming period, it tends therefore to favour regions with high absorption rate past tracks when it comes to the allocation decision (Dellmuth (2011)). Charron (2016) shows that even Member States do not have full interest to go against the full absorption policy goal of the European Commission to send a good signal of the use of the EU funds to the European Commission. As a result, Member States push to foster absorption rate of EU funds in recipient regions, even the poorest ones. Resorting to *restrospective projects* or reducing regional share of contribution illustrate the strategic behaviours aiming at fastening absorption.

## 5 Conclusions

This study investigates the effects of EU funds on regional growth in Objective 1 NUTS-2 regions with a panel dataset of 244 regions for the period 2000-16 by using a RDD with heterogeneous treatment based on the methodology of Becker et al. (2013). We focus on the speed of the EU funds' absorption that has been approached as the share of real payments allocated for a given programming period implemented after the end of this corresponding programming period.

The main result of this study is that a faster absorption of the EU funds reduces the effectiveness of the Cohesion Policy in Objective 1 regions, or the ability of the EU funds to stimulate economic growth. This result validates that fast absorption might be the outcome of a strategic behaviour of recipient regions or governments aiming at increasing absorption rates to send a signal of good management to the European authorities (Huliaras & Petropoulos (2016); Aivazidou et al. (2020)). This finding gives ground to the conflict between spending fast and spending good in lagging regions as they are generally characterised by a lower absorption capacity (Becker et al. (2013)). A more detailed analysis suggests that this result is especially valid in regions with the lowest economic growth performances, the latter being mostly located in the Mediterranean Europe. A second result is that slow absorption has a negative impact on economic growth in non-treated regions. As they are wealthier, they receive significantly less EU transfers and are generally characterised by a higher absorption capacity (Becker et al. (2012)), which gives little room to conduct the strategic behaviours aiming at fastening absorption. Therefore, in non-treated regions, slow absorption would rather be the outcome of a lower management quality (Milio (2007); Tosun (2014); Surubaru (2017); Incaltarau et al. (2020)). A third result is that the treatment does not have any robust direct impact on regional economic growth, making its impact purely conditional. Indeed, the magnitude of the impact of the EU funds in lagging regions is strongly determined by their pace of spending. This finding is in line with a large majority of the literature underlining the conditional effectiveness of the Cohesion Policy (see e.g., Cappelen et al. (2003); Becker et al. (2013); Rodriguez-Pose & Garcilazo (2015); Becker et al. (2018)).

Regarding policy implications, we believe that the decommitment rule suffers from a major design issue: it is characterised by a *one-size fits all* logic. The early work Batterbury (2002) already mentioned the need of a place-based approach ("The Commission needs to adapt better its Structural Fund policies to suit the characteristics of particular regions having diverse cultures and norms" (Batterbury (2002), p.15), that has been applied in several areas of the Cohesion Policy since the Barca report (Barca (2009)). Therefore, a differentiated decommitment rule between Objective 1 and wealthier regions, or even a suspension of the rule for the Objective 1 regions, could help to mitigate the use of strategies detrimental to the effectiveness of the Cohesion Policy. This would be especially relevant for the period 2021-27 as the budget allocated to the Cohesion Policy would globally be reduced but increasingly focused on the lagging regions, a trend likely to be valid for future programming periods.

## 6 Disclosure statement

No potential conflict of interest was reported by the author.

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## 7 Data availability

Data of this manuscript are available with the following private link: https://figshare.com/s/86248080da4c6581f694

### Notes

<sup>1</sup>From the *Programme of the Commission for 1989.* Address by Jacques Delors, President of the European Commission, to the European Parliament and his reply to the debate. Strasbourg, 16 February 1989.

<sup>2</sup>Final report - ERDF and CF expenditure. Contract No 2007.CE.16.0.AT.036.

 $^3 \rm The$  financial implementation of the EU Funds is even updated on a daily basis by the European Commission. See https://cohesiondata.ec.europa.eu/overview#

<sup>4</sup> It should be mentioned that the n+2 rule states that a sum committed to a programme should be claimed by the end of the second year following a given programming period. Therefore, because of the European authorities' processing time, last payments are executed 3 years after the end of a given programming period (2002 for 1994-1999, 2009 for 2000-2006 and 2016 for 2007-2013).

 $^5$  See the EU Council Regulations 595/2006 and 189/2007 for instance.

<sup>6</sup>This is not problematic for the programming period 2007-13 as the latest payments are made in 2016.

<sup>7</sup>Another potential jump visible at around 60% of the European average per capita GDP could be pointed. Such a jump is observed in other related studies (see, *e.g.* Becker et al. (2010), Gagliardi & Percoco (2017), Percoco (2017)). However, this is out of the scope of studying the impact of the Objective 1 treatment on regional growth as we are focused on the 75% threshold.

 $^8\mathrm{For}$  sake of brevity, the test values are not reported. They are available upon request.

# 8 Tables

Table 1:	Descriptive	statistics
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Variable	Obs.	Mean	S.D.	Minimum	Maximum
GDP per capita growth	747	0.049	0.037	-0.141	0.221
Investment per capita growth	705	0.046	0.072	-0.267	0.428
Objective 1	747	0.275	0.447	0	1
Eligibility for Objective 1	747	0.313	0.464	0	1
Relative GDP per capita	747	0.934	0.328	0.291	2.603
GBYS	722	0.010	0.015	-0.006	0.105
Activity rate	730	0.692	0.078	0.403	0.828
Unemployment rate	726	0.088	0.056	0.019	0.348
Population density	720	357.5	778.081	3.300	7394.000
Human capital	730	0.240	0.092	0.036	0.519
Share of manufacturing in GVA	747	0.219	0.086	0.035	0.535
Share of financial and business services in GVA	747	0.226	0.060	0.092	0.476
Share of late payments	747	0.432	.362	0	1
Below GDP 75% threshold	203	0.473	0.430	0	1
Above GDP 75% threshold	544	0.417	0.332	0	1
Below sample mean	377	0.126	0.167	0	0.429
Above sample mean	370	0.744	0.208	0.433	1

*Notes*: Detailed descriptive statistics are provided for the share of late payments.

Source: Own calculations based on data from European Commission, Eurostat and Cambridge Econometrics.

Table 2: Heterogeneity of the Objective 1 treatment effect on regional GDP per capita growth: sample decomposition according to the share of late payments.

	(1)	(2)
Estimator	Late payments below the average	Late payments above the average
RDD	0.016***	0.019***
	(0.003)	(0.003)
Panel fixed-effects	-0.008	0.026***
	(0.008)	(0.008)
Observations	313	419
RDD 50-100	0.004	0.017***
	(0.006)	(0.004)
Observations	157	237

Notes: This table reports results from the two stage least square estimation of the LATE with a sample restricted to the observations with a share of late payments below (column (1)) and above (column (2)) the European average. RDD refers to the estimation of the Local Average Treatment Effect (LATE) of the Objective 1 treatment for the entire sample, while RDD 50-100 considered only the observations with a relative GDP per capita between 50% and 100% of the European average. The forcing variable is the relative GDP per capita of 1996-98 (97-99) for years 2000-06, 2000-02 for years 2007-13 and 2007-09 for years 2014-16. Panel fixed effects describes the two stage least square (panel IV) estimation using regional fixed effects.

The dependent variable presents regional GDP per capita growth. Robust standard errors are reported in parentheses. \* denotes p < 0.10; \*\* p < 0.05; \*\*\*p < 0.01.

Source: Own calculations based on data from European Commission and Eurostat.

Table 3: Objective 1, late payments and regional GDP per capita growth– heterogeneous local average treatment effect (HLATE) (IV second stage estimates) and panel fixed-effects.

	(1) HLATE 25%	(2) HLATE 25%	(3) HLATE 50%	(4) HLATE 50%	(5) Panel FE	(6) Panel FE
GDP per capita	0.061	0.059	-0.055**	-0.057**	-0.115***	-0.116***
	(0.120)	(0.120)	(0.023)	(0.022)	(0.019)	(0.018)
Objective 1	0.027	0.022	0.001	0.001	0.008	-0.007
	(0.024)	(0.019)	(0.001)	(0.001)	(0.008)	(0.009)
Late payments	-0.013	-0.001	-0.016**	-0.016**	$-0.019^{***}$	-0.016***
	(0.011)	(0.015)	(0.007)	(0.007)	(0.006)	(0.006)
Objective 1 <sup>*</sup> Late payments	$0.031^{**}$	0.027	$0.027^{***}$	$0.025^{***}$	0.022***	$0.018^{***}$
• • •	(0.014)	(0.016)	(0.009)	(0.010)	(0.006)	(0.007)
Late $payments^2$	· · · ·	-0.019		-0.008	. ,	-0.019
Late pagmente		(0.045)		(0.018)		(0.012)
Objective 1* Late $payments^2$		0.037		0.033		0.095***
Objective i Late payments		(0.065)		(0.030)		(0.018)
Density	0.018	0.018	0.014	0.013	-0.005	-0.016
Density	(0.030)	(0.030)	(0.020)	(0.010)	(0.010)	(0.015)
Unemployment	-0.050	-0.040	-0.066*	-0.058	0.028	0.010
Onemployment	(0.060)	(0.058)	(0.038)	(0.037)	(0.028)	(0.010)
Activity	0.037	0.043	0.000	0.001	-0.090**	-0.127***
receivity	(0.037)	(0.039)	(0.026)	(0.025)	(0.045)	(0.045)
Financial sector	0.070	0.076	0.025	0.029	(0.045) 0.135	(0.043) $0.177^*$
i manetar sector	(0.056)	(0.061)	(0.032)	(0.033)	(0.102)	(0.105)
Manufacturing sector	0.035	0.038	(0.032) $0.042^{***}$	0.045***	(0.102) $0.211^{***}$	(0.105) $0.271^{***}$
Manufacturing sector	(0.033)	(0.023)	(0.042)	(0.043)	(0.063)	(0.066)
Tertiary education	0.025	0.023	$0.058^{***}$	(0.017) $0.059^{***}$	0.190***	$0.197^{***}$
reitiary education	(0.020)	(0.023)	(0.020)	(0.035)	(0.030)	(0.031)
Spread Germany (GBYS)	-0.358***	-0.375***	-0.389***	$-0.402^{***}$	-0.807***	-0.808***
Spread Germany (GD15)	(0.109)	(0.110)	(0.077)	(0.080)	(0.113)	(0.117)
	(0.103)	(0.110)	(0.077)	(0.080)	(0.115)	(0.117)
Constant	0.019	0.021	0.033***	0.034***	0.048***	0.059***
Constant			0.000	0.00-	0.0 -0	0.000
$R^2$	(0.015)	(0.013)	(0.005)	(0.004)	(0.008)	(0.10)
	$0.047 \\ 2.954^*$	$0.044 \\ 4.242^{***}$	0.273	0.273 20.681***	0.461 28.327***	0.469
Weak instruments			19.180***			18.946***
Durbin Endogeneity	4.672*	5.599	3.293	3.498	4.080	17.504
Wu-Hausman Endogeneity	2.169	1.926	1.600	1.118	1.424	4.307
Regional fixed effects	NO	NO	NO	NO	YES	YES
Observations	219	219	394	394	732	732

Notes: This table reports results from the two stage least square estimation of the HLATE with a sample restricted to 12.5% (columns (1)-(2)) and 25% (columns (3)-(4)) around the 75\% threshold of the forcing variable (GDP per capita). The forcing variable is the relative GDP per capita of 1996-98 (97-99) for years 2000-06, 2000-02 for years 2007-13 and 2007-09 for years 2014-16. The two stage least square (panel IV) estimation using regional fixed-effects are reported in columns (5) and (6) using the full sample. The dependent variable presents regional GDP per capita growth.

Robust standard errors are reported in parentheses. \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01.

Table 4: Objective 1, late payments and regional GDP and Investment per capita growth–Spatial autoregressive (SAR) fixed-effects (IV second stage estimates).

	(1)	(2)	(3)	(4)
GDP per capita	-0.085***	-0.085***	-0.059*	-0.056*
	(0.013)	(0.013)	(0.031)	(0.030)
Objective 1	0.011**	0.004	0.035***	0.002
-	(0.005)	(0.006)	(0.011)	(0.014)
Late payments	-0.008**	-0.007*	0.005	0.011
1 0	(0.004)	(0.004)	(0.009)	(0.010)
Objective 1 <sup>*</sup> Late payments	0.010*	0.008	0.005	-0.004
5 1 0	(0.006)	(0.006)	(0.010)	(0.014)
Late $payments^2$	. ,	-0.008		-0.064**
		(0.013)		(0.031)
Objective 1 <sup>*</sup> Late $payments^2$		0.041*		0.198***
		(0.022)		(0.052)
Density	-0.008	-0.006	-0.005	-0.007
	(0.013)	(0.012)	(0. 028)	(0.028)
Unemployment	0.003	0.003	$0.252^{*}$	$0.259^{**}$
	(0.055)	(0.054)	(0.130)	(0.130)
Activity	-0.053	-0.056	0.031	0.014
	(0.058)	(0.057)	(0.136)	(0.134)
Financial sector	$0.214^{**}$	$0.215^{**}$	-0.086	-0.010
	(0.087)	(0.087)	(0.209)	(0.208)
Manufacturing sector	0.027	0.040	0.044	0.099
	(0.061)	(0.062)	(0.144)	(0.144)
Tertiary education	$0.149^{***}$	$0.152^{***}$	$0.220^{***}$	$0.217^{**}$
	(0.035)	(0.036)	(0.085)	(0.014)
Spread Germany (GBYS)	-0.788***	-0.786***	$-1.529^{***}$	$-1.518^{***}$
	(0.116)	(0.115)	(0.282)	(0.277)
$R^2$	0.105	0.115	0.119	0.146
$\rho$ dep. variable	$0.690^{***}$	$0.696^{***}$	$0.598^{***}$	$0.583^{***}$
$\rho$ residuals	$0.747^{***}$	$0.728^{***}$	$0.692^{***}$	$0.680^{***}$
Regional fixed effects	YES	YES	YES	YES
Observations	732	732	732	732

Notes: This table reports results from the Spatial auto-regressive fixed effects model where the dependent variable is GDP per capita growth (columns (1)-(2)) and Investment per capita growth(columns (3)-(4)).  $\rho$  dep. variable denotes the spatial lag coefficient for the dependent variable, the same logic applies for  $\rho$  residuals. Their significances legitimate the use of the SAR model.

Robust standard errors are reported in parentheses. \*p < 0.1, \*\*p< 0.05, \*\*\*p< 0.01.

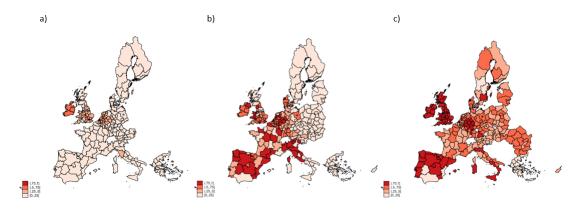


Figure 1: Share of late EU payments of MFFs 1994-99 (a), 2000-06 (b) and 2007-13 (c). *Notes*: MFF denotes for Multi-annual Financial Framework. [0.25; 0.5] denotes a NUTS-2 region where between 25% and 50% of total EU payments of a given MFF (1994-99, 2000-06 or 2007-13) have been executed after the end of this MFF. The same logic applies for [0; 0.25], [0.5; 0.75] and [0.75;1]. *Source*: Own elaboration based on data from Lo Piano et al. (2017). (c) EuroGeographic EuroGeographics for the administrative boundaries.



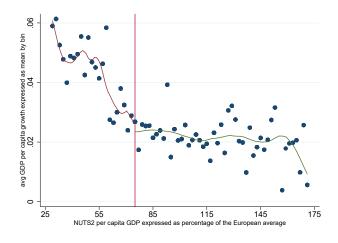


Figure 2: Discontinuity of outcome at the threshold

*Notes:* The graph shows the GDP per capita growth plotted on the forcing variable with annual pooled data of programming periods 2000-16.

Source: Own elaboration based on data from Eurostat and Cambridge Econometrics.

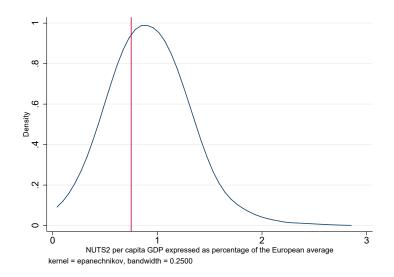


Figure 3: Density check to detect potential manipulation of GDP per capita *Notes:* The graph shows a density plot of relative GDP per capita based on the years determining the treatment status of a NUTS-2 region with pooled data of the period 2000-16. *Source:* Own elaboration based on data from Eurostat.

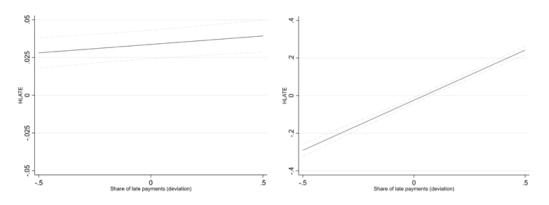


Figure 4: HLATE and regional per capita GDP growth for different levels of the share of late EU payments.

*Notes*: The solid line illustrates the point estimates, the dashed lines represent the 95 percent confidence intervals. The confidence intervals are derived from bootstrapped standard errors with 100 replications. *Source:* Own elaboration.

# 10 Appendices

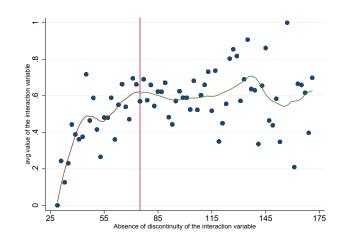


Figure A1 : Absence of discontinuity of the interaction variable

*Notes:* The graph shows the share of late payments plotted on the forcing variable with annual pooled data of programming periods 2000-16.

Source: Own elaboration based on data from Lo Piano et al. (2017).

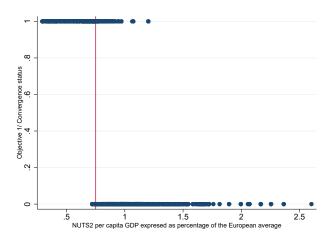


Figure A2 : Assignment of Objective 1 treatment status

*Notes:* The graph shows the assignment of the actual treatment status (1 if a NUTS-2 region is treated, 0 in the other case) with annual pooled data of programming periods 2000-16.

Source: Own elaboration based on Eurostat and from EU regulations displayed in Table A1 .

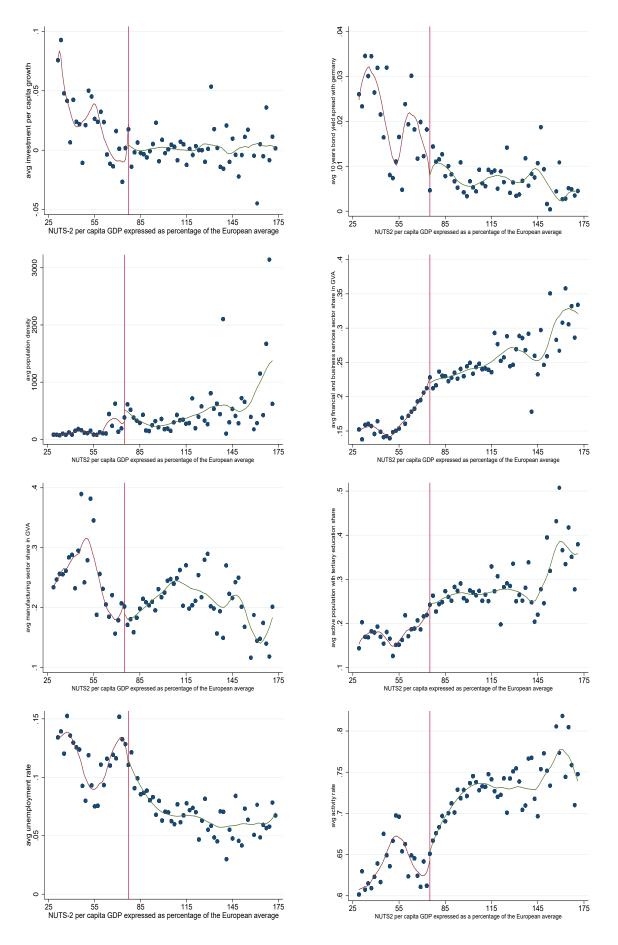


Figure A3 : Discontinuity of per capita investment growth and absence of discontinuity of the covariates at the threshold level

*Notes:* The graph shows the covariates used in the analysis plotted on the forcing variable with averaged pooled data of programming periods 2000-06, 2007-13 and the period 2014-16. *Source:* Own elaboration based on data from Cambridge Econometrics and Eurostat.

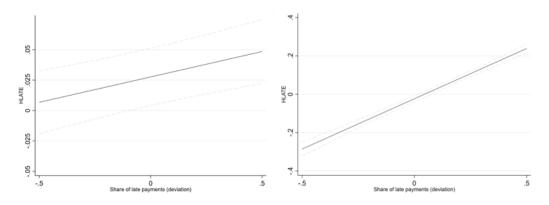


Figure A4 : HLATE and regional per capita investment growth for different levels of the share of late EU payments.

*Notes*: The solid line illustrates the point estimates, the dashed lines represent the 95 percent confidence intervals. The confidence intervals are derived from bootstrapped standard errors with 100 replications. *Source*: Own elaboration.

Variable	Variable definition	Source
GDP per capita growth	An annual averaged percentage variation of current GDP per capita in PPS calculated as the difference between the log GDP per capita in PPS and its lagged value for a given MFF (Multi-annual Financial	Author's calculations based on Eurostat and Cambridge Econometrics if missing data from Eurostat
Investment per capita growth	Framework). An annual averaged percentage variation of regional current gross fixed capital formation (GFCF) per capita in PPS calculated as the difference the log GFCF per capita in PPS and its lagged value for a given MFF.	Author's calculations based on Eurostat and Cambridge Econometrics if missing data from Eurostat
Objective 1 status	An averaged dummy variable being equal to 1 if a region receives ac- tually the Objective 1 treatment for a given MFF.	Official Journal of the European Communities L, 194, Volume 53, 27.7.1999 (2000-06) and L, 243, Volume 44, 6.9.2006 (2007-13)
Late EU real payments	An averaged share of the allocated budget of a given MFF that has actually been spent after the last year of this given MFF.	Authors' calculations based on Lo Piano et al. (2017)
Relative GDP per capita	A share of regional GDP per capita in PPS relatively to the European average. (i) Years 1994-96 for the MFF 2000-06 (97-99 for new countries), (ii) years 2000-02 for the MFF 2007-13 and (iii) years 2007-09 for MFF 2014-16.	Authors' calculations based on Eurostat
Spread Germany (GBYS)	An annual averaged difference in percentage between a region's national 10 year bond and the German one for a given MFF.	Authors' calculations based on Eurostat
Activity rate	An annual averaged regional share of the population employed and unemployed for a given MFF.	Cambridge Econometrics
Unemployment rate	An annual averaged regional share of the population unemployed for a given MFF.	Cambridge Econometrics
Population density	An annual averaged number of inhabitants per squared km for a region in a given MFF.	Cambridge Econometrics
Tertiary education	An annual averaged regional share of the active population with tertiary education for a given MFF.	Cambridge Econometrics
Manufacturing sector	An annual averaged regional share of the manufacturing sector in the regional gross added value for a given MFF.	Cambridge Econometrics
Financial and business services sector	An annual averaged regional share of the financial and business services sector in the regional gross added value for a given MFF.	Cambridge Econometrics

Table A1 : Variables definition and data sources

Sources: Own elaboration.

Table A2 : Objective 1, late payments and regional Investment per capita growth– heterogeneous local average treatment effect (HLATE) (IV second stage estimates) and panel fixed-effects.

	(1) HLATE 25%	(2) HLATE 25%	(3) HLATE 50%	(4) HLATE 50%	(5) Panel FE	(6) Panel FE
GDP per capita	-0.147	-0.153	-0.071	-0.074	-0.078***	-0.078***
	(0.248)	(0.241)	(0.054)	(0.053)	(0.025)	(0.025)
Objective 1	0.001	-0.016	0.022	-0.014	0.034*	-0.005
5	(0.052)	(0.040)	(0.021)	(0.013)	(0.020)	(0.021)
Late payments	-0.020	-0.000	-0.014	-0.000	-0.011	0.002
F = 5	(0.023)	(0.031)	(0.014)	(0.016)	(0.010)	(0.011)
Objective 1* Late payments	0.063**	0.041	0.056***	0.045**	0.038***	0.024
Objective i Late payments	(0.031)	(0.037)	(0.020)	(0.022)	(0.015)	(0.016)
Late $payments^2$	(0.051)	-0.010	(0.020)	-0.052	(0.013)	(0.010) -0.075***
Late payments-						
Objective 1* Late $payments^2$		$(0.084) \\ 0.176$		$(0.038) \\ 0.127^*$		(0.026) $0.260^{***}$
Objective 1 <sup>+</sup> Late payments <sup>-</sup>						
David	0.052	(0.132) 0.052	0.034	(0.065) 0.030	0.065	(0.041) 0.153
Density						
TT	(0.063)	(0.061)	$(0.049) \\ -0.169^*$	(0.050)	(0.020) $0.264^{**}$	(0.287) $0.236^{**}$
Unemployment	-0.158	-0.111		-0.134		
A	(0.126)	(0.121)	(0.094)	(0.094)	(0.119)	(0.113)
Activity	-0.029	-0.000	-0.050	-0.029	0.029	-0.057
	(0.082)	(0.084)	(0.064)	(0.064)	(0.116)	(0.118)
Financial sector	-0.055	-0.032	-0.048	-0.040	-0.234	-0.149
	(0.110)	(0.119)	(0.070)	(0.071)	(0.212)	(0.211)
Manufacturing sector	0.033	0.045	0.052	0.059	0.223*	0.372***
	(0.047)	(0.049)	(0.037)	(0.038)	(0.117)	(0.121)
Tertiary education	0.116*	0.103	0.161***	0.158***	0.322***	0.320***
	(0.067)	(0.070)	(0.042)	(0.044)	(0.065)	(0.069)
Spread Germany (GBYS)	-0.781***	-0.855***	-0.710***	-0.751***	-1.456***	-1.459***
	(0.243)	(0.240)	(0.196)	(0.199)	(0.266)	(0.271)
Constant	0.020	0.031	0.014	0.019*	0.029	0.056**
Constant	(0.020)	(0.031)	(0.014)	(0.019)	(0.029)	$(0.036^{++})$
$R^2$	0.230	(0.020) 0.229	(0.012) 0.220	(0.011) 0.223	(0.020) 0.357	(0.022) 0.373
Weak instruments	$2.954^{*}$	0.229 4.242	19.180	20.681	0.357 28.327	0.575 18.946
Durbin Endogeneity	0.537	$\frac{4.242}{0.954}$	19.180 1.914	20.081 2.265	28.327 4.887*	$15.571^{***}$
Wu-Hausman Endogeneity	0.537 0.245	$0.954 \\ 0.293$	0.909	0.723	$4.887^{+}$ 1.765	15.571*** 3.792***
	0.245 NO	0.293 NO	0.909 NO	0.723 NO	1.765 YES	3.792*** YES
Regional fixed effects						
Observations	219	219	394	394	732	732

*Notes*: This table reports results from the two stage least square estimation of the HLATE with a sample restricted to 12.5% (columns (1)-(2)) and 25% (columns (3)-(4)) around the 75% threshold of the forcing variable (GDP per capita). The forcing variable is the relative GDP per capita of 1996-98 (97-99) for years 2000-06, 2000-02 for years 2007-13 and 2007-09 for years 2014-16. The two stage least square (panel IV) estimation using regional fixed-effects are reported in columns (5) and (6) using the full sample. The dependent variable presents regional Investment per capita growth.

Robust standard errors are reported in parentheses. \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01.

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Table

$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	-0.0308 (0.037) 0.207 (0.018) -0.025* (0.013) 0.057*** (0.018) (0.018) (0.018) (0.018) -0.323****	$\begin{array}{c} -0.051\\ -0.051\\ (0.047)\\ -0.002\\ (0.018)\\ (0.018)\\ (0.018)\\ (0.019)\\ (0.018)\\ (0.019)\\ 0.036\\ (0.027)\\ -0.048\\ (0.040)\\ 0.063\\ (0.033)\\ 0.007\\ -0.003\\ 0.007\\ 0.003$	$\begin{array}{c} -0.045^{***} \\ (0.011) \\ 0.012^{**} \\ (0.005) \\ 0.000 \\ (0.004) \\ (0.006) \\ (0.006) \\ 0.006 \\ (0.014) \end{array}$	-0.037*** (0.013) 0.008 (0.007) -0.004 (0.003) 0.005 (0.005) 0.005 (0.010) 0.009 (0.010) 0.008 (0.010) 0.008 (0.017)	$-0.094^{**}$ (0.038) 0.020 (0.020) -0.004 (0.011) 0.024 (0.024) (0.024) (0.024)	$\begin{array}{c} -0.080^{**} \\ (0.039) \\ (0.013) \\ 0.013 \\ (0.016) \\ -0.005 \\ -0.005 \\ (0.011) \\ (0.011) \\ 0.013 \\ (0.016) \\ (0.016) \\ (0.006) \\ (0.006) \end{array}$
	(0.037) (0.037) (0.018) -0.025* (0.018) (0.018) (0.018) (0.018) (0.018) (0.059) -0.323***	$\begin{array}{c} (0.047) \\ -0.002 \\ (0.018) \\ -0.018 \\ (0.019) \\ (0.019) \\ (0.027) \\ -0.048 \\ (0.040) \\ 0.040) \\ 0.167** \\ (0.083) \\ 0.007 \\ 0.007 \\ 0.003 \end{array}$	$\begin{array}{c} (0.011) \\ (0.012^{**} \\ (0.005) \\ (0.004) \\ (0.006) \\ (0.006) \\ (0.014) \end{array}$	$\begin{array}{c} 0.013)\\ 0.008\\ 0.007\\ 0.004\\ (0.003)\\ 0.005\\ 0.003\\ 0.003\\ 0.003\\ 0.003\\ 0.009\\ (0.010)\\ 0.008\\ (0.010\\ 0.008\\ (0.017)\\ 0.008\end{array}$	(0.038) (0.020) (0.020) (0.011) (0.024) (0.024) (0.024) (0.024)	$\begin{array}{c} (0.039) \\ 0.013 \\ (0.016) \\ -0.005 \\ (0.011) \\ 0.016 \\ (0.013) \\ 0.073 \\ (0.016) \\ 0.073 \\ (0.016) \\ 0.006 \\ 0.006 \\ \end{array}$
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	(0.018) -0.025* (0.013) 0.057*** (0.018) (0.018) -0.009 (0.059) -0.323***	$\begin{array}{c} (0.018) \\ -0.018 \\ (0.019) \\ 0.036 \\ (0.027) \\ -0.048 \\ (0.027) \\ -0.040 \\ (0.040) \\ 0.167** \\ 0.167** \\ (0.083) \\ 0.007 \\ (0.050) \\ 0.007 \\ (0.033) \end{array}$	(0.005) 0.000 (0.004) 0.002 (0.006) 0.006 (0.014)	$\begin{array}{c} (0.007) \\ -0.004 \\ (0.003) \\ 0.005 \\ (0.005) \\ 0.030^{***} \\ (0.010) \\ 0.009 \\ (0.020) \\ 0.008 \\ (0.017) \end{array}$	(0.020) -0.004 (0.011) 0.024 (0.024) -0.004	$\begin{array}{c} (0.016) \\ -0.005 \\ (0.011) \\ 0.016 \\ (0.013) \\ 0.073 \\ (0.016) \\ 0.073 \\ (0.016) \\ 0.073 \\ (0.069) \end{array}$
$ \begin{array}{cccccc} \text{yments} & -0.037^{***} & -0.032^{***} & -0.025^{*} \\ & (0.012) & (0.010) & (0.013) \\ \text{ve} 1^{*} \text{Late payments} & 0.050^{***} & 0.057^{***} & 0.057^{***} \\ & (0.016) & (0.0137) & (0.018) \\ \text{yments}^{2} & 0.038^{*} & 0.057^{***} & 0.057^{***} \\ & (0.016) & (0.018) & 0.018 \\ \text{ve} 1^{*} \text{Late payments}^{2} & 0.035 & 0.038 \\ \text{ve} 1^{*} \text{Late payments}^{2} & (0.035) & 0.098^{*} \\ & (0.052) & 0.008^{*} & -0.009 \\ \text{othert} & 0.0018 & 0.005^{*} & -0.009 \\ \text{othert} & 0.0018 & 0.006 & 0.0117 \\ & (0.021) & (0.020) & (0.050) \\ \text{othert} & 0.018 & -0.008 & -0.117 \\ & (0.031) & (0.040) & (0.096) \\ \text{al sector} & 0.016 & -0.012 \\ & (0.052) & (0.062) & (0.066) \\ \end{array} $	-0.025* (0.013) 0.057*** (0.018) -0.009 (0.059) -0.323***	$\begin{array}{c} -0.018\\ (0.019)\\ 0.036\\ (0.027)\\ -0.048\\ (0.040)\\ 0.167**\\ (0.083)\\ 0.063)\\ \hline 0.007\\ (0.050)\\ 0.033***\end{array}$	0.000 (0.004) 0.006) (0.006) 0.006 (0.014)	-0.004 (0.003) 0.005 (0.005) $0.030^{***}$ (0.010) 0.009 (0.020) 0.008 (0.017)	-0.004 (0.011) 0.024 (0.024) (0.024)	$\begin{array}{c} -0.005 \\ (0.011) \\ 0.016 \\ (0.013) \\ 0.073 \\ (0.016) \\ 0.073 \\ (0.069) \\ 0.006 \\ 0.006 \\ 0.006 \end{array}$
ve 1* Late payments $(0.012)$ $(0.010)$ $(0.013)$ ve 1* Late payments $0.050^{***}$ $0.038^{***}$ $0.057^{***}$ $yments^2$ $(0.016)$ $(0.0137)$ $(0.018)$ $yments^2$ $(0.035)$ $(0.018)$ ve 1* Late $payments^2$ $(0.035)$ $(0.035)$ ve 1* Late $payments^2$ $(0.035)$ $(0.035)$ $0.098^*$ $(0.035)$ or $1^{*}$ $(0.002)$ $(0.009)$ or $0.002^*$ $(0.059)$ or $0.002^*$ $(0.059)$ or $0.018^*$ $(0.031)$ $(0.040)$ $(0.050)$ (0.040) $(0.096)1177$ $(0.031)$ $(0.040)$ $(0.096)1177$ $(0.031)$ $(0.040)$ $(0.096)1200^{*} (0.065) (0.065)$	$\begin{array}{c} (0.013) \\ 0.057^{***} \\ (0.018) \\ -0.009 \\ (0.059) \\ -0.323^{****} \\ (0.120) \end{array}$	$\begin{array}{c} (0.019) \\ 0.036 \\ 0.027) \\ -0.048 \\ (0.040) \\ 0.167^{**} \\ (0.083) \\ 0.007 \\ (0.000) \\ 0.007 \\ 0.033^{***} \end{array}$	(0.004) 0.002 (0.006) 0.006 (0.014)	$\begin{array}{c} (0.003)\\ 0.005\\ (0.005)\\ 0.030^{***}\\ (0.010)\\ 0.009\\ (0.020)\\ 0.008\\ (0.017)\end{array}$	(0.011) 0.024 (0.024) (0.024)	$\begin{array}{c} (0.011) \\ 0.016 \\ (0.013) \\ 0.073 \\ (0.016) \\ 0.073 \\ (0.069) \\ 0.006 \\ 0.006 \\ 0.0006 \end{array}$
ve 1* Late payments $0.050^{***}$ $0.038^{***}$ $0.057^{***}$ $yments^2$ $(0.016)$ $(0.0137)$ $(0.018)$ $yments^2$ $(0.035)$ $-0.028$ $(0.035)$ ve 1* Late $payments^2$ $(0.035)$ $(0.035)$ ve 1* Late $payments^2$ $(0.032)$ $(0.052)$ $(0.052)$ $0.004^*$ $0.002^*$ $-0.009$ oyment $0.0021$ $(0.02)$ $(0.059)$ oyment $0.018$ $-0.008$ $-0.117$ (0.040) $(0.096)al sector -0.013 (0.040) (0.096)(0.061)$ $(0.040)$ $(0.096)(0.060)$	0.057*** (0.018) -0.009 (0.059) -0.323***	$\begin{array}{c} 0.036\\ (0.027)\\ -0.048\\ (0.040)\\ 0.167^{**}\\ (0.083)\\ 0.007\\ (0.050)\\ 0.07\end{array}$	0.002 (0.006) 0.006 (0.014)	0.005 (0.005) 0.030*** (0.010) 0.009 (0.020) (0.017)	0.024 (0.024) -0.004	0.016 (0.013) 0.073 (0.016) 0.073 (0.069) 0.006
$yments^2 \qquad \begin{array}{ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c} (0.018) \\ -0.009 \\ (0.059) \\ -0.323^{***} \\ (0.120) \end{array}$	(0.027) -0.048 (0.040) 0.167** (0.083) 0.007 (0.050) 0.033***	(0.006) 0.006 (0.014)	$\begin{array}{c} (0.005) \\ 0.030^{***} \\ (0.010) \\ 0.009 \\ 0.008 \\ 0.008 \\ (0.017) \end{array}$	(0.024) -0.004	(0.013) 0.073 (0.016) 0.073 (0.069) 0.006
$yments^2 = -0.028 \\ ve 1^* Late payments^2 = 0.008^* \\ 0.035 \\ 0.098^* \\ 0.008^* = 0.003^* \\ 0.002 \\ 0.002 \\ 0.002 \\ 0.002 \\ 0.002 \\ 0.003 \\ 0.008 \\ -0.117 \\ 0.008 \\ 0.018 \\ 0.016 \\ 0.0117 \\ 0.006 \\ 0.017 \\ 0.006 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000 \\ 0.000$	-0.009 (0.059) -0.323***	$\begin{array}{c} -0.048\\ (0.040)\\ 0.167**\\ (0.083)\\ 0.007\\ (0.050)\\ -0.203***\end{array}$	0.006 (0.014)	0.030*** (0.010) 0.009 (0.020) 0.008 (0.017)	-0.004	0.073 (0.016) 0.073 (0.069) 0.006
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$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	-0.009 (0.059) -0.323*** (0.120)	(0.083) 0.007 (0.050) -0.293***	0.006 (0.014)	(0.020) 0.008 (0.017)	-0.004	(0.069) 0.006 (0.008)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	-0.009 (0.059) -0.323*** (0.120)	0.007 (0.050) _0.23***	0.006 (0.014)	0.008 (0.017)	-0.004	0.006
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	(0.059) -0.323*** (0.120)	(0.050) _0 293***	(0.014)	(0.017)		(000)
$\begin{array}{ccccc} -0.134^{**} & -0.088 & -0.323^{***} \\ (0.061) & (0.086) & (0.120) \\ -0.018 & -0.008 & -0.117 \\ (0.031) & (0.040) & (0.096) \\ -0.013 & 0.016 & -0.027 \\ (0.052) & (0.062) & (0.066) \end{array}$	$-0.323^{***}$ (0.120)	-0 993***	· · ·	(	(0.040)	(07070)
$ \begin{array}{ccccc} (0.061) & (0.086) & (0.120) \\ -0.018 & -0.008 & -0.117 \\ (0.031) & (0.040) & (0.096) \\ -0.013 & 0.016 & -0.027 \\ (0.052) & (0.062) & (0.066) \end{array} $	(0.120)	0.4.00	-0.096**	-0.094***	-0.061	-0.063
$\begin{array}{cccc} -0.018 & -0.008 & -0.117 \\ (0.031) & (0.040) & (0.096) \\ -0.013 & 0.016 & -0.027 \\ (0.052) & (0.062) & (0.066) \end{array}$		(0.102)	(0.041)	(0.025)	(0.101)	(0.130)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	-0.117	-0.101	-0.005	0.014	0.041	0.081
$\begin{array}{cccc} -0.013 & 0.016 & -0.027 \\ (0.052) & (0.062) & (0.066) \end{array}$	(0.096)	(0.064)	(0.028)	(0.017)	(0.067)	(0.059)
(0.062) $(0.066)$	-0.027	-0.002	-0.045	-0.041	-0.259***	-0.232***
	(0.066)	(0.091)	(0.031)	(0.027)	(0.058)	(0.062)
$0.056^{**}$ $0.029$	0.029	0.081	0.013	0.010	-0.067**	-0.079**
(0.028) $(0.039)$	(0.039)	(0.064)	(0.018)	(0.014)	(0.030)	(0.038)
$0.080^{***}$ $0.094$	0.094	$0.108^{***}$	$0.080^{***}$	$0.074^{***}$	$0.165^{***}$	$0.171^{***}$
(0.026) $(0.057)$ $($	(0.057)	(0.038)	(0.025)	(0.019)	(0.042)	(0.045)
** -0.774*** -1.500***	-1.500***	$-1.481^{***}$	-0.338**	-0.323***	-0.167	-0.170
(0.116) $(0.111)$	(0.230)	(0.308)	(0.134)	(0.066)	(0.281)	(0.300)
Constant $0.024^{***}$ $0.027^{***}$ $-0.017^{*}$ $-0.009$	-0.017*	-0.009	$0.042^{***}$	$0.038^{***}$	$0.041^{***}$	$0.033^{***}$
(0.005) $(0.004)$ $(0.010)$ $(0.008)$	(0.010)	(0.008)	(0.003)	(0.003)	(0.009)	(0.008)
$R^2$ 0.237 0.249 0.199 0.209	0.199	0.209	0.205	0.220	0.160	0.179
Observations 394 394 394 394	394	394	394	394	394	394

*Notes*: This table reports results from quantile regressions and contains an estimate of the VCE via bootstrapping, the VCE includes between-quantile blocks. The dependent variable presents regional per capita GDP growth (columns (1)-(2)-(5)-(6)) and investment per capita growth (columns (3)-(4)-(7)-(8)). The estimations are conducted on regions having a GDP per capita between 50% and 100% of the European average. Robust standard errors are reported in parentheses. \*p < 0.1, \*\*p < 0.05, \*\*\*p < 0.01.

Table A4 : Objective 1, late payments and outcome variables– Objective 1 treatment intensity.		
Table A4. Objective 1. fate payments and outcome variables Objective 1 treatment intensity.	Table A4. Objective 1 late normants and outcome remiables. Objective 1 treatme	nt intendity
	Table A4. Objective 1, late payments and outcome variables - Objective 1 treatme	nu muensiuv.

	(1) Low intensity	(2) Low intensity	(3) High intensity	(4) High intensity
GDP per capita	-0.108***	-0.081	-0.063**	-0.080***
	(0.027)	(0.069)	(0.025)	(0.026)
Objective 1	0.031	-0.375	0.029**	0.013
	(0.021)	(0.735)	(0.013)	(0.013)
Late payments	-0.018***	-0.023***	0.013	0.012
1.0	(0.007)	(0.008)	(0.011)	(0.013)
Objective 1 <sup>*</sup> Late payments	-0.419	9.612	-0.003	-0.005
	(0.579)	(18.040)	(0.012)	(0.014)
Late $payments^2$		-0.003		-0.019
Late payments		(0.021)		(0.030)
Objective 1 <sup>*</sup> Late $payments^2$		37.519		0.083**
e bjeenve i nade pagmende		(69.360)		(0.034)
Density	-0.015	-0.012	-0.002	-0.005
	(0.015)	(0.016)	(0.020)	(0.020)
Unemployment	-0.615**	-0.504**	0.107	0.074
I U	(0.308)	(0.246)	(0.065)	(0.067)
Activity	-0.341**	-0.993	0.005	-0.048
	(0.116)	(1.203)	(0.089)	(0.089)
Financial sector	0.375	0.004*	0.209	0.276*
	(0.318)	(0.514)	(0.161)	(0.162)
Manufacturing sector	0.382***	0.815	0.218**	0.289***
0	(0.076)	(0.726)	(0.092)	(0.094)
Tertiary education	0.249***	0.383	-0.008	0.039 <sup>´</sup>
-	(0.067)	(0.258)	(0.051)	(0.054)
Spread Germany (GBYS)	0.130	0.441	-0.801***	-0.846***
	(0.409)	(0.785)	(0.134)	(0.135)
Constant	0.025***	0.042***	0.012	$0.034^{**}$
	(0.006)	(0.026)	(0.016)	(0.016)
Weak instruments	8180.850***	4042.240***	<sup>*</sup> 12.911 <sup>***</sup>	8.521***
Durbin Endogeneity	3.579	2.058	$10.941^{***}$	$13.015^{***}$
Wu-Hausman Endogeneity	4.512**	0.543	$3.319^{*}$	$3.090^{**}$
$R^2$	0.421	0.507	0.501	0.527
Observations	366	366	366	366

*Notes*: This table reports results from the two stage least square (panel IV) estimation using regional fixed-effects. Objective 1 treatment intensity is lower than its median value (0.15 % of GDP per capita) in columns (1)-(2) and higher in (columns (3)-(4)). The dependent variable presents regional GDP per capita growth.

Robust standard errors are reported in parentheses. \*p < 0.1, \*\*p< 0.05, \*\*\*p< 0.01.