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## ABSORPTIVE CAPACITY AND THE GROWTH EFFECTS OF REGIONAL TRANSFERS: A REGRESSION DISCONTINUITY DESIGN WITH HETEROGENEOUS TREATMENT EFFECTS

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# ABSORPTIVE CAPACITY AND THE GROWTH EFFECTS OF REGIONAL TRANSFERS: A REGRESSION DISCONTINUITY DESIGN WITH HETEROGENEOUS TREATMENT EFFECTS

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# ABSTRACT

## Absorptive Capacity and the Growth Effects of Regional Transfers: A Regression Discontinuity Design with Heterogeneous Treatment Effects*

Transfers to individuals, firms, and regions are often regulated by threshold rules, giving rise to a regression discontinuity design. An example are transfers provided by the European Commission to regions of EU member states below a certain income level. Researchers have focused on estimation of the average treatment effect of this program, assuming that it does not vary in a systematic way across units. We suggest a regression discontinuity design which allows for parametric or nonparametric identification of heterogeneous average treatment effects that systematically vary with observable characteristics in order to shed light on the role of absorptive capacity in determining the impact of regional transfers on economic growth across regions in the European Union. The results suggest that only about 47% of the regions, namely those with a sufficiently high endowment with human capital and a high quality of government, are able to turn transfers under the Union's Objective 1 Structural Funds programme into faster growth. Those regions are the ones which are responsible for a positive average effect of the programme.

JEL Classification: C21, H54, O40 and R11
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# 1 Introduction

Economic growth is considered to depend on a region's absorptive capacity. A higher level of absorptive capacity facilitates technology transfer and thereby stimulates catch-up processes (see Benhabib and Spiegel, 1994; Griffith, Redding and van Reenen, 2004; and Becker, Hornung, and Woessmann, 2011). Similarly, we expect the response of economic growth to fiscal stimuli in general and transfers in specific to depend on a targeted region's absorptive capacity, The reason is that higher levels of human capital and quality of government may enable a recipient region to use funds more efficiently.[1] The critical role of absorptive capacity in this wide interpretation surfaces in both the literatures on growth and convergence and the one on economic effects of aid (see Burnside and Dollar, 2000, 2004). While views may differ with regard to the sources of higher absorptive capacity and the exact channels through which it promotes economic prosperity, there is unequivocal agreement about a positive role of higher absorptive capacity in the form of better education or higher endowments with skilled labor and better economic, judicial, or political institutions for economic growth. Also, while there is mixed support for the benefit of transfers from developed to less developed countries or regions,[2] proponents and opponents would agree that transfers targeted towards countries or regions will generate a marginal return on investment which is ceteris paribus higher in regions with a higher absorptive capacity.[3]

In this paper, we provide evidence on the relevance of absorptive capacity for regional economic growth by looking at European Union transfers to sub-national regions. The European Commission takes a number of initiatives to pursue its goals of growth and convergence. Such initiatives are subsumed under two major funding programmes: the Structural Funds – which are composed of the European Regional Development Fund (ERDF) and the European Social Fund – and the Cohesion Fund. In this project, we single out one budget among the Structural Funds – which is referred to as Objective 1 – for the following reasons. First, the Objective 1 program is the biggest initiative among the aforementioned pools. Second, its goal is most clearly directed to provide transfers to the poorest regions of the EU to allow them to catch up with the EU average. Third, it exhibits

[1] We interpret absorptive capacity in a very broad sense, including endowments with human capital and a country's or region's ability to translate stimuli into economic activity using best-practice technologies as well as institutional characteristics which prevent misuse of resources in unproductive ways.

[2] For instance, see Dalgaard, Hansen, and Tarp (2004) who argue in favor of an aid-growth link, and Easterly (2003) who questions the effectiveness of aid with respect to economic growth.

[3] The direct link between political institutions and growth as discussed, for instance, in Mauro (1995) and Acemoglu, Johnson, and Robinson (2005) is not at the center of this study. We focus on the role of political institutions for transfer effectiveness.

a treatment discontinuity which may be used for identification of a local average treatment effect: only so-called NUTS2 regions[4] whose per-capita GDP is below 75% of the EU average are eligible for funding while regions above the 75% threshold are not eligible.[5] We used this design in Becker, Egger, and von Ehrlich (2010) to identify the local average treatment effect of Objective 1 funding on average annual growth of per-capita income measured at the treatment threshold. The main finding was that, on average, Objective 1 treatment raises growth in the neighborhood of the threshold and, according to a back-of-the-envelope calculation (which assumes that tax collection and transfers are organized in a non-distorting way) exhibits a positive net effect. However, what we are interested in here is not a single local *average* treatment effect (LATE) but estimation of *heterogeneous* local average treatment effects (HLATE). In particular, we wish to infer how the treatment effect of regional transfers varies with *absorptive capacity* of targeted regions.

The paper contributes to two literatures. First, it formulates a flexible regression discontinuity design (RDD) which is applicable with fixed but arbitrary numbers of forcing variables, i.e. the variables determining treatment status. It also allows for fixed but arbitrary numbers of variables the treatment effect interacts with. For such designs, we formulate an RDD for the HLATE and illustrate that nonparametric estimators work comparatively well relative to parametric estimators of the multivariate control function, even in small to medium-sized samples. Not surprisingly, parametric estimators – if the functional form of the relationship between forcing and treatment variable is known – work slightly better than their nonparametric counterparts in terms of root mean squared error, but the HLATE estimates appear to have small biases in our simulations with one or two treatment interaction terms. Obviously, with regional per-capita income levels prior to a programming period as one forcing (threshold) variable and Objective 1 treatment interaction with two measures of absorptive capacity, the application of interest here is a special case of that general design. Second, with regard to the literature on growth effects of transfer treatment – such as national or regional aid, of which EU Objective 1 transfer are a prominent example – we shed light on the quantitative importance of absorptive capacity in terms of human capital endowments and quality of government as two measures of absorptive capacity for the treatment effect of transfers on economic growth.

The empirical application reveals a great variability of the impact of Objective 1

[4]NUTS is the acronym for *N*omenclature des *U*nités *T*erritoriales *S*tatistiques coined by EUROSTAT which refers to regional aggregates. NUTS2 regions correspond to groups of counties and unitary authorities with a population of 0.8-3 million inhabitants.

[5]Funding periods are called Programming Periods in EU jargon and last for 5 to 7 years. The three most recent Programming Periods were 1989-1993, 1994-1999 and 2000-2006. Eligibility is determined in pre-specified years prior to a Programming Period.

treatment on regional growth that is related to absorptive capacity as measured by a region's endowment with human capital and with regional quality of government. Higher positive effects of Objective 1 transfers are realized in regions with above-average levels of human capital endowments and quality of government relative to other regions. The LATE of Objective 1 tends to be insignificantly different from zero for other regions.

The remainder of the paper is organized as follows. In the next section, we outline the econometric model with RDDs for the HLATE in general terms. An Appendix provides evidence on the small sample performance in terms of bias and root mean squared error for identification of the HLATE in the distribution of treatment effects with nonparametric versus parametric control functions. In Section 3, we apply this identification strategy for the HLATE to a sample of NUTS2 regions of 25 EU countries and evaluate the role of absorptive capacity for the effectiveness of Objective 1 transfers for regional economic growth. Section 4 concludes with a summary of our main findings.

# 2 RDD for heterogeneous treatment effects

Our focus is on identification of heterogeneous treatment effects with an RDD where the heterogeneity of treatment effects pertains to interactions with exogenous observable variables. A standard fuzzy RDD, which contains the sharp RDD as a limiting case, exploits discontinuities in the probability of treatment conditional on *one* forcing variable. The result is a research design where the rule giving rise to the discontinuity becomes an instrumental variable for the actual treatment status. In a fuzzy RDD, one can identify a local average treatment effect (LATE) in the sense of Imbens and Angrist (1994). LATE is the average treatment effect for *compliers*, i.e. those treated who take the treatment only when eligible, but do not get treated when ineligible. Our aim is to employ estimators, where the estimated treatment effect is not (only) local in the sense of being a LATE, but local and heterogenous in the sense that it is allowed to vary with a fixed but arbitrary number of observables. Accordingly, we refer to this as a heterogenous local average treatment effect (HLATE). We will allow heterogeneity of treatment effects to vary with variables that do or do not influence treatment status. Moreover, for the sake of generality, we will consider the case of a fixed but arbitrary number of forcing variables (and, hence, discontinuities at potentially more than one treatment threshold) as well as a fixed but arbitrary number of exogenous variables interacting with the treatment effect.

In the following, we the outline parametric as well as nonparametric identification for the most general case with many forcing variables and many variables affecting the treatment effects. Building on this, we compare the performance of the derived estimators in Monte Carlo studies (see Appendix C) where we focus on designs which permit graphical illustration.[6]

## 2.1 Definition of heterogeneous local average treatment effects (HLATE)

Let us use the following notation. First, use $T_i$ to denote a treatment indicator which is equal to one if treatment is received by unit $i$ and zero otherwise. Outcome $y_i$ is a function of treatment, of the $1 \times K$ vector $\mathbf{x_i}$ of forcing variables, and of the $1 \times L$ vector $\mathbf{z_i}$ of interaction variables that render treatment more or less effective but do not affect treatment assignment. We seek to estimate the heterogenous local average treatment effect

$$HLATE(\mathbf{x_i} = \mathbf{x_0}, \mathbf{z_i}) = HLATE(\mathbf{x_0}, \mathbf{z_i}) = E[y_{1i}|\mathbf{x_0}, \mathbf{z_i}] - E[y_{0i}|\mathbf{x_0}, \mathbf{z_i}] \qquad (1)$$

where $y_{1i}$ denotes the outcome with treatment and $y_{0i}$ the outcome without treatment and $\mathbf{x_0}$ denotes the $1 \times K$ vector of threshold values $x_{0k}$ for the $K$ forcing variables.

The challenge for treatment evaluation arises because we observe each individual $i$ only in one of two mutually exclusive states of the world, either with or without treatment, and treatment assignment is not random but depends on the information in $\mathbf{x_i}$. In contrast to the commonly identified local average treatment effect (LATE), the HLATE above allows for variation in the dimensions of $\mathbf{z}_i$. This flexibility is particularly valuable as in many cases where the LATE is not different from zero, the HLATE may vary substantially around the LATE.

In the RDD, the treatment probability is a discontinuous function of the forcing variables

$$P(T_i = 1|\mathbf{x_i}) = \begin{cases} g_1(\mathbf{x_i}) & \text{if } x_{ik} \geq x_{0k} \ \forall \ k \in K \\ g_0(\mathbf{x_i}) & \text{otherwise} \end{cases} \qquad (2)$$

where $x_{0k}$ represents the threshold value of the $k$-th forcing variable with $k = 1, ..., K$. The literature distinguishes two types of RDD: the sharp design where $g_1(\mathbf{x_0}) - g_0(\mathbf{x_0}) = 1$ and the fuzzy design where $0 < g_1(\mathbf{x_0}) - g_0(\mathbf{x_0}) < 1$. Accordingly, in the sharp design, the treatment probability jumps from zero to one once all $K$ treatment rules are satisfied while the probability jump is less than one in the fuzzy design where treatment assignment is noisy due to exemptions from the rules.

[6]Obviously, with more than two variables enforcing treatment status or co-determining treatment effects, graphical illustration becomes difficult. Specifically, we will illustrate two scenarios in the Appendix: a *1-way threshold* scenario where the forcing variable is independent of the variable that interacts with the treatment effect, and a *2-way threshold* scenario with two forcing variables, one of which is allowed to simultaneously affect the magnitude of treatment effects.

Regardless of whether a sharp or a fuzzy design prevails, the HLATE can be estimated parametrically or non-parametrically under the following assumptions:

**Assumption 1** *(Continuity of counterfactual outcomes at threshold vector.)* $E[y_0]$ *and* $E[y_1]$ *are continuous at* $\mathbf{x_0}$.

This is the standard identifying assumption in an RDD. In Becker, Egger, and von Ehrlich (2010), we provided evidence that, in the context of the effect of Objective 1 treatment on regional growth, there were no jumps in a number of observable covariates at the 75% threshold in compliance with Assumption 1.

**Assumption 2** *(Continuity of interaction variables at threshold vector.)* *The interaction variables* $\mathbf{z_i}$ *are continuous at* $\mathbf{x_0}$.

This assumption is important for the HLATE to pick up genuine variation in the interaction variables. In our application, we check this assumption by plotting graphs for human capital and quality of government to see whether these measures of absorptive capacity are discontinuous about the forcing variable at the threshold or not (see Figure 2 below).

**Assumption 3** *(Random assignment of interaction variables* $\mathbf{z_i}$ *conditional on* $\mathbf{x_i}$.*)* *The interaction variables* $\mathbf{z_i}$ *are uncorrelated with the error term in the outcome equation, conditional on* $\mathbf{x_i}$.

In the context of our application, this assumption states that, conditional on GDP per capita (the forcing variable), regions with different human capital endowments and quality of governance do not differ in unobserved dimensions which are relevant for per-capita income growth. Take the example of two regions with the same pre-treatment level of GDP per capita that differ in their human capital endowment. The fact that, despite different human capital endowment, they achieved the same pre-treatment GDP per capita indicates that there were other factors which, in the past, led the two regions to achieve the same pre-treatment level of GDP per capita. For instance, regions in former communist countries with high human capital endowments might have achieved the same (low) per-capita income as some Western European regions with low human capital endowments. The omitted factor would be the past experience of a communist system in place. Assumption 3 states that such other factors are not systematically contributing contemporaneously to economic growth. We address this particular concern in several ways: first, we run fixed effects regressions (amongst others) which wipe out time-constant factors such as past communist political system experience. Furthermore, we take the absorptive capacity interaction variables as time-constant variables, so that the HLATE picks up factors that facilitate or hinder the effective use of EU transfers over longer horizons. Both human capital endowment and quality of government are factors which hardly vary over time and are thus relatively stable attributes of regions.

In the following we outline the estimation approaches formally, where the sharp RDD can be understood as a special case of the fuzzy RDD with treatment assignment being a deterministic function of the forcing variables while the fuzzy design allows for some randomness in treatment assignment.

## 2.2 Parametric control function for identification of the HLATE

Assuming that $E[y_i|\mathbf{x_i}, \mathbf{z_i}]$ follows an additive process based on polynomial functions of the columns of $\mathbf{x_i}$ and $\mathbf{z_i}$ we can write the conditional expected outcomes in the counterfactual situations of treatment and non-treatment as follows:

$$E[y_{0i}|\mathbf{x_i}, \mathbf{z_i}] = \alpha + \mathbf{f_0}(\widetilde{\mathbf{x}}_\mathbf{i}) + \mathbf{h_0}(\overline{\mathbf{z}}_\mathbf{i}) \tag{3}$$

$$E[y_{1i}|\mathbf{x_i}, \mathbf{z_i}] = E[y_{0i}|\mathbf{x_i}, \mathbf{z_i}] + \beta + \mathbf{f_1^*}(\widetilde{\mathbf{x}}_\mathbf{i}) + \mathbf{h_1^*}(\overline{\mathbf{z}}_\mathbf{i}) \tag{4}$$

where $\mathbf{f_0}(\widetilde{\mathbf{x}}_\mathbf{i})$, $\mathbf{h_0}(\overline{\mathbf{z}}_\mathbf{i})$, $\mathbf{f_1^*}(\widetilde{\mathbf{x}}_\mathbf{i})$, and $\mathbf{h_1^*}(\overline{\mathbf{z}}_\mathbf{i})$ are sufficiently smooth polynomial functions of the columns of $\mathbf{x_i}$ and $\mathbf{z_i}$.[7] In order to simplify the interpretation of the coefficients, we define the parametric functions $\mathbf{f_0}(\cdot)$ and $\mathbf{f_1^*}(\cdot)$ in terms of deviations of $x_{ik}$ from the thresholds $x_{0k}$ and $\mathbf{h_0}(\cdot)$ and $\mathbf{h_1^*}(\cdot)$ in terms of deviations of $z_{il}$ from the sample means $E[\mathbf{z}_l]$. Accordingly, $\widetilde{x}_{ik} = x_{ik} - x_{0k}$ and $\overline{z}_{il} = z_{il} - E[\mathbf{z}_l]$. Overall, we can then write

$$E[y_i|\mathbf{x_i}, \mathbf{z_i}] = E[y_{0i}|\mathbf{x_i}, \mathbf{z_i}] + T_i[\beta + \mathbf{f_1^*}(\widetilde{\mathbf{x}}_\mathbf{i}) + \mathbf{h_1^*}(\overline{\mathbf{z}}_\mathbf{i})]. \tag{5}$$

Using this notation, the local average treatment effect at the multidimensional threshold level of the forcing variables, $\mathbf{x_0}$, is given by $\beta$. The heterogenous treatment effect for deviations from the sample means in the z-dimensions is measured by $HLATE(\mathbf{x_0}, \mathbf{z_i}) = \beta + \mathbf{h_1^*}(\overline{\mathbf{z}}_\mathbf{i})$.

In the sharp RDD, where the treatment is a deterministic function of the set of forcing variables, we can estimate the treatment effects by the following regression:

$$y_i = \alpha + \mathbf{f_0}(\widetilde{\mathbf{x}}_\mathbf{i}) + \mathbf{h_0}(\overline{\mathbf{z}}_\mathbf{i}) + T_i\left[\beta + \mathbf{f_1^*}(\widetilde{\mathbf{x}}_\mathbf{i}) + \mathbf{h_1^*}(\overline{\mathbf{z}}_\mathbf{i})\right] + \epsilon_i \tag{6}$$

$$where\ T_i = 1(x_{ik} \geq x_{0k}\ \forall\ k \in K) \tag{7}$$

[7]We use a notation where $\mathbf{f_1^*}(\cdot) \equiv \mathbf{f_1}(\cdot) - \mathbf{f_0}(\cdot)$ and $\mathbf{h_1^*}(\cdot) \equiv \mathbf{h_1}(\cdot) - \mathbf{h_0}(\cdot)$, and where $\mathbf{f_1}(\cdot)$ and $\mathbf{h_1}(\cdot)$ in the treatment state are defined analogously to $\mathbf{f_0}(\cdot)$ and $\mathbf{h_0}(\cdot)$ in the no-treatment state. More generally, one can also allow for interaction terms between columns of $\mathbf{x_i}$ and $\mathbf{z_i}$ and add those interaction terms as additional elements in a (new) $\mathbf{z_i}$ with larger column space. Hence, we will not specifically address this issue. But we note that, in our application, all results are robust to the introduction of interaction terms between (polynomials of) the forcing variable and (polynomials of) the measures of absorptive capacity.

In the fuzzy RDD, even though the treatment probability jumps when crossing the multidimensional threshold $\mathbf{x_0}$, as indicated in (2), $T_i$ is no longer a deterministic function of $\mathbf{x_0}$. Hence, the identifying assumption of the sharp RDD in (7) is violated. This requires us to specify some functional form for the conditional treatment probability $P(T_i = 1|\mathbf{x_i})$. Let us define a scalar $R_i = 1(x_{ik} \geq x_{0k}\ \forall\ k \in K)$ indicating whether *all rules* underlying the treatment status are fulfilled or not. When $g_1(\mathbf{x_i})$ and $g_0(\mathbf{x_i})$ in (2) can be approximated sufficiently well, $R_i$ may serve as an instrument for $P(T_i = 1|\mathbf{x_i})$ conditional on $g_1(\mathbf{x_i})$ and $g_0(\mathbf{x_i})$. Using analogous notation as for the outcome, we may determine $\mathbf{g_0}(\widetilde{\mathbf{x}}_\mathbf{i})$, $\mathbf{g_1^*}(\widetilde{\mathbf{x}}_\mathbf{i}) \equiv \mathbf{g_1}(\widetilde{\mathbf{x}}_\mathbf{i}) - \mathbf{g_0}(\widetilde{\mathbf{x}}_\mathbf{i})$, $\mathbf{l_0}(\overline{\mathbf{z}}_\mathbf{i})$, $\mathbf{l_1^*}(\overline{\mathbf{z}}_\mathbf{i}) \equiv \mathbf{l_1}(\overline{\mathbf{z}}_\mathbf{i}) - \mathbf{l_0}(\overline{\mathbf{z}}_\mathbf{i})$. In the first stage of the 2SLS implementation of the fuzzy RDD we estimate:[8]

$$T_i = \mathbf{g_0}(\widetilde{\mathbf{x}}_\mathbf{i}) + \mathbf{l_0}(\overline{\mathbf{z}}_\mathbf{i}) + R_i[\delta + \mathbf{g_1^*}(\widetilde{\mathbf{x}}_\mathbf{i}) + \mathbf{l_1^*}(\overline{\mathbf{z}}_\mathbf{i})] + \nu_i \tag{8}$$

The forcing variables are again measured in terms of deviations from the respective thresholds. Substituting (8) for the treatment indicator $T_i$ in (6) we obtain the reduced form for the fuzzy RDD. Equations (6) and (8) together constitute the IV estimator of the $HLATE(\mathbf{x_0}, \mathbf{z_i})$.

## 2.3 Nonparametric control function for identification of the HLATE

The parametric estimates of the treatment effects rely on the validity of the approximations $\mathbf{f_0}(\cdot)$, $\mathbf{f_1^*}(\cdot)$, $\mathbf{h_0}(\cdot)$, $\mathbf{h_1^*}(\cdot)$, $\mathbf{g_0}(\cdot)$, $\mathbf{g_1^*}(\cdot)$, $\mathbf{l_0}(\cdot)$, and $\mathbf{l_1^*}(\cdot)$. As has been shown by Hahn, Todd, and van der Klaauw (2001), average treatment effects can be identified nonparametrically under much weaker assumptions (basically only continuity restrictions). This section introduces the nonparametric approach to the estimation of the HLATE.

In a standard RDD with one forcing variable, where $\mathbf{x_i}$ is a scalar and $\mathbf{z_i}$ is absent from the model, identification and consistent estimation of the LATE hinges upon estimation of $E[y_i|x_i]$. In the more general design analyzed here, we have to estimate $E[y_i|\mathbf{x_i}, \mathbf{z_i}]$ in the neighborhood of the multidimensional discontinuity. It can be shown that the HLATE at the multidimensional threshold is given by (see Appendix A for a proof):

$$HLATE(\mathbf{x_0}, \mathbf{z_i}) = \lim_{\mathbf{\Delta} \to \mathbf{0}} \frac{E[y_i|\mathbf{0} < \widetilde{\mathbf{x}}_\mathbf{i} < \mathbf{\Delta}, \mathbf{z_i}] - E[y_i| - \mathbf{\Delta} < \widetilde{\mathbf{x}}_\mathbf{i} < \mathbf{0}, \mathbf{z_i}]}{E[T_i = 1|\mathbf{0} < \widetilde{\mathbf{x}}_\mathbf{i} < \mathbf{\Delta}, \mathbf{z_i}] - E[T_i = 1| - \mathbf{\Delta} < \widetilde{\mathbf{x}}_\mathbf{i} < \mathbf{0}, \mathbf{z_i}]} \tag{9}$$

[8]Alternatively, the first stage may be estimated by a nonlinear model. In our application, the results remain unaffected by the choice of a linear or nonlinear first stage.

where $\boldsymbol{\Delta}$ denotes a vector of some small, positive deviations from zero. In the sharp RDD the denominator in (9) is simply unity whereas it ranges between zero and one in the fuzzy RDD.

As pointed out by Hahn, Todd, and van der Klaauw (2001), standard kernel estimators for the above conditional expectations to the left and the right of the threshold yield biased estimates for the treatment effects due to their adverse boundary properties. At boundary points the kernel estimators have a slower rate of convergence than at interior points. Therefore, Hahn, Todd, and van der Klaauw (2001) propose using local linear regressions instead of standard kernel estimates. In our case with multiple interaction and forcing variables we resort to multivariate local polynomial regressions as introduced by Ruppert and Wand (1994).

Let us collect all columns in $\widetilde{\mathbf{x}}_\mathbf{i}$ and in $\overline{\mathbf{z}}_\mathbf{i}$ in the vector $\boldsymbol{\xi}_i$. The first $K$ columns of $\boldsymbol{\xi}_i$ belong to the columns of $\widetilde{\mathbf{x}}_\mathbf{i}$ and the second $L$ columns belong to $\overline{\mathbf{z}}_\mathbf{i}$. We aim at estimating the expectations of $y_i$ in the neighborhood of the multidimensional threshold for given values of $\overline{\mathbf{z}}_\mathbf{i}$. Hence, we fit a polynomial in the neighborhood of a vector $\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{0}$. The local linear estimator for $\lim_{\boldsymbol{\Delta}\to 0} E[y_i|\mathbf{0} < \widetilde{\mathbf{x}}_\mathbf{i} < \boldsymbol{\Delta}, \overline{\mathbf{z}}_\mathbf{i}]$ is given by:

$$\min_{b_0,\mathbf{b}_1} \sum_{i=1}^{N} \{y_i - b_0 - \mathbf{b}_1^T \boldsymbol{\xi}_i\}^2 \mathbf{K}_\mathbf{H}(\boldsymbol{\xi}_i) * 1(\widetilde{\mathbf{x}}_\mathbf{i} > \mathbf{0}) \tag{10}$$

where $\mathbf{K}_\mathbf{H}$ represents a kernel function with bandwidth matrix $\mathbf{H}$. In our applications, we generally use a uniform kernel. For further details on the use of local polynomial regressions we refer to Härdle, Müller, Sperlich, and Werwatz (2004). $HLATE(\mathbf{x_0}, \mathbf{z_i})$ is asymptotically normally distributed as shown in Appendix B.

# 3 The HLATE of EU Objective 1 transfers depending on absorptive capacity

In this section, we provide parametric and nonparametric estimates of the LATE and the HLATE of Objective 1 treatment on regional growth within the EU. The latter allows for heterogeneity of the response to Objective 1 treatment depending on human capital endowments or regional quality of government, our two measures of absorptive capacity.

## 3.1 Data and descriptive evidence

We use data on NUTS2 regions for the last three completed EU programming periods: 1989-93, 1994-99, and 2000-06. Due to enlargements of the EU during the observation period, the number of NUTS2 regions covered varies between 186 and 279 per period. Hence, a regional unit may be observed in the data once, twice, or thrice. Of course, repeated observation of cross-sectional units should be respected in estimation either by clustering of standard errors or alternative treatment of fixed region-specific effects. For instance, with re-sampling of the standard errors, one should use a routine which re-samples the data in blocks (across all years; see Fitzenberger, 1998; and Becker and Egger, 2011, for an application).

For the question of interest, we utilize four types of data from two sources. First, information on NUTS2 regional per-capita GDP at purchasing power parity (PPP) is available from the Regional Database compiled by Cambridge Econometrics. The corresponding data can be utilized to calculate the level of regional average per-capita income in the years specified by the European Commission prior to each programming period – the forcing variable for Objective 1 treatment eligibility. NUTS2 regions whose per-capita GDP fell short of 75% of the EU average were eligible to receive Objective 1 funds from the EU. The same regional GDP data can be employed to determine average annual growth of per-capita income in PPP terms during a programming period.

Second, information about actual Objective 1 treatment is available directly from the European Commission, from various Council Regulations, in particular the Regulations numbered 2052/88, 2082/93, and 502/1999, and in editions of the Official Journal (see also Becker, Egger, and von Ehrlich, 2010). The data show that there is a discrepancy between the rule and actual treatment, which establishes a fuzziness: about 7% of the data points represent non-compliers with the 75% assignment rule.

Third, since our emphasis is on absorptive capacity in terms of a region's human capital endowment, we employ data on the level of education of the workforce in a region from the European Union Labour Force Survey. More specifically, we employ data on the share of workers with at least secondary education[9] and allow the response to Objective 1 treatment to vary with it.

Fourth, regional quality of government (QoG) data come from Charron and Lapuente (2011). They use a perception-based indicator of QoG built from a 34,000-

[9]Eurostat delivered NUTS2-level data on education of the workforce for the years 1999 through 2008. Education is measured in three categories, based on UNESCO's International Standard Classification of Education (ISCED): low education refers to ISCED categories 0-2. Medium education refers to ISCED categories 3 and 4 and high education to ISCED categories 5 and 6. Our measure of (at least) upper-secondary education includes ISCED categories 3 to 6. In our sample of NUTS2 EU regions, the correlation coefficient between the share of the work force with at least upper-secondary education in 1999 and in 2008 is 0.91, which shows the stability of human capital endowment over time and makes it an interesting stable measure of the absorptive capacity of a region.

respondents survey. Their data-set is available for download and contains information at the national level for all 27 EU countries and, at the sub-national level, for 172 NUTS 1 and NUTS 2 regions in the European Union for the year 2009.[10] The variable is standardized within the EU (mean of 0 and standard deviation of 1), such that higher scores equal higher levels of QoG. The QoG index is based on 16 separate survey questions pertaining to three key public services – education, health care, and law enforcement. The respondents were asked to rate their public services with respect to three related concepts of QoG – the quality, impartiality, and level of corruption of the above-mentioned services.

Both human capital and quality of government indicators are used as time-invariant variables. The reason is that data for both of those variables is not available for all years for all regions. With respect to human capital we have data for several years which we average over time.[11] In contrast, the quality of government indicator is only available for one year.

Summary statistics for all variables used in our application are provided in Table 1. As in Section 2, we measure absorptive capacity variables – human capital (HC) and quality of government (QoG) – as deviations from the sample mean. The forcing variable corresponds to average GDP per capita in the threshold years that were crucial to assigning eligibility for Objective 1 transfers. Table 1 reports per-capita GDP in the threshold years in absolute terms and as a fraction of average EU per capita GDP. The Objective 1 treatment variable indicates transfer recipience. GDP per capita growth is measured in nominal terms in the average year of the budgetary period and represents our outcome of interest.

– Table 1 –

In terms of specification, our estimation corresponds to the case of a 1-way treatment threshold (in the forcing variable GDP per capita relative to the EU average) in Section 2 and an interaction with one or two regressors. In fact, we present results separately for three cases: (a) human capital as the only indicator of absorptive capacity; (b) quality of government as the only indicator of absorptive capacity; (c) both human capital and quality of government as indicators of absorptive capacity which matter simultaneously.

[10] Countries with NUTS 1 level information are Belgium, Germany, Greece, Hungary, Netherlands, Sweden, and United Kingdom. NUTS2 level information is available for Austria, Bulgaria, Czech Republic, Denmark, France, Italy, Poland, Portugal, Slovak Republic, Romania, and Spain. We assume that quality of government is at least as time invariant as human capital endowment.

[11] We averaged human capital for each region across the years. This minimizes also the problem of unequal spacing of missing data on human capital across regions and time.

A difference with respect to the Monte Carlo analysis in Appendix C lies in the use of repeated observations of cross-sectional units which we allow for in order to exploit variability in the data (taking account of repeated observations in the computation of standard errors throughout).

– Figure 1 and 2 –

Before turning to regressions, it is useful to have a look at the raw data when pooling them across all three programming periods. Figure 1 depicts the fraction of treated observations against their initial per-capita GDP relative to the EU average – in bins of a width of 1.5 percentage points in the forcing variable – in the years critical for determining Objective 1 eligibility. The discontinuity at 75% is evident, but the design is fuzzy because a number of regions does not comply with the treatment rule.

Such a discontinuity does not appear when plotting equivalent graphs for human capital and quality of government (see Figure 2). Note that this supports Assumption 2 underlying the HLATE, which requires the interaction variables to be continuous at the forcing variables threshold.

In a similar vein, in Becker, Egger, and von Ehrlich (2010), we showed graphs depicting the absence of jumps in other covariates, supporting Assumption 1. We do not repeat them here for space constraints, but refer the reader to Figure 4 of that paper.

– Figure 3 –

Unlike RDD plots for homogeneous LATE, the graphs in Figure 3 are three-dimensional figures, similar to those shown in the Monte Carlo analysis in Appendix C. They are useful to visualize the interaction between the forcing variable (initial GDP/capita relative to the EU average in a period), the variables relating to absorptive capacity (education and quality of government as deviations from the respective EU average), and the outcome variable (GDP per capita growth). Notice that this figure is generated for the subspace of values of HC and QoG where we have relatively good support (see Figure 13 in the Appendix for frequency plots of the data) Since the rule is not applied sharply by the Commission, we expect both treated units (marked by red dots) and untreated units (marked by blue dots) just above and below the threshold of the forcing variable (i.e., at a level of 0.75 or 75%). The surfaces are estimated using 5th-order polynomial functions in the forcing variable and linear functions of the absorptive capacity variables. These surfaces are estimated separately for both sides of the threshold in order to allow for a discontinuity.

The figure clearly points to a continuous impact of the forcing variable on the outcome, and to a discontinuity at the 75% threshold which in turn varies significantly with absorptive capacity. The data indicate a smaller (or even non-existent) treatment effect at the threshold for regions with below-average absorptive capacity and a higher treatment effect for regions with above-average absorptive capacity. The wedges between the two surfaces in the human capital and quality of government plots indicate heterogeneity of LATE. Note, however, that the HLATE cannot be directly “inferred” from the wedges in Figure 3. The wedges between the surfaces disregard fuzziness about Objective 1 status, i.e., the true treatment effect needs to take account of the size of the jump in the treatment probability at the 75% threshold.

Hence, we proceed with parametric instrumental variable regression analysis and with nonparametric regression analysis to avoid a possibly large bias of the heterogeneous treatment effects accruing to fuzziness.

## 3.2 Regression results

A first step to scrutinize the heterogeneity of treatment effects displayed in Figure 3 is to split the sample into observations featuring below- and above-average absorptive capacity and to estimate the LATE for each of these subsamples separately using the fuzzy RDD estimator. Regarding the human capital employed here, we observe 355 observations with an above-average HC endowment and 319 observations below the average level of HC. The former group exhibits an LATE of about 2.5 percentage points – significant at the 1 percent level – while the LATE of the latter group amounts to about 1.2 percentage points which turns out to be significant at the 10 percent level. Regarding quality of government, the 418 observations with an above-average level of QoG feature a LATE of 2.2 percentage points – significant at the 1 percent level – while the LATE for the group of below-average QoG turns out to be insignificant at the usual levels of confidence. These results point to a considerable heterogeneity of treatment effects. Yet, the split of the sample may seem arbitrary and we loose substantive information and efficiency by collapsing the two continuous measures of absorptive capacity into binary indicators. A more efficient way to take into account the heterogeneity of the LATE is to follow the identification strategy for the HLATE as introduced in Section 2.

The regression results of are summarized in Tables 2-4 for polynomial IV regressions and in Tables 5 and 6 for nonparametric regressions.

– Tables 2-6 –

Table 2 contains eighteen different parametric specifications that form the basis for LATE and HLATE estimation. Different columns refer to different degrees of the polynomial in the forcing variable (initial per-capita GDP) and to pooled regression versus fixed effects panel estimation. In the vertical dimension, we use three different types of specifications where we vary the polynomial degree of the interaction variable, human capital (HC): linear (panel 1), quadratic (panel 2), cubic (panel 3).[12] The treatment effect as well as the linear interaction between treatment and absorptive capacity are highly significant in each of the specifications. In contrast to the cubic interaction between treatment and absorptive capacity, the quadratic interaction turns out to be insignificant.

Overall, the estimates reveal a considerable heterogeneity of LATE for different levels of absorptive capacity. Taking the pooled OLS specification with a 5th-order polynomial function of the forcing variable and a cubic function of HC as the benchmark, a one standard deviation of absorptive capacity yields a 82% higher treatment effect compared to the average level of HC. Note that a statement like this is not possible in the simple approach where the sample is ex ante split in a high HC and a low HC subsample.

An important issue related to the interpretation of our findings is whether human capital is indeed key in making good use of the funds assigned by the EU or whether human capital might already be a factor in attracting EU funds, conditional on a region qualifying for Objective 1 status. In fact, we can correlate the amount of funds received (relative to a region's initial GDP) under Objective 1 to the region's human capital endowment. Using data from the programming periods 1994-1999 and 2000-2006 for which we know the amount of funds received per region, we find a negative correlation between human capital endowment and funds received relative to GDP in the group of Objective 1 regions. Our findings of a stronger growth effect of Objective 1 status are thus not explained by more funds received, but by the more efficient use of the given funds.

Table 3 is similar to Table 2, but uses quality of government (QoG) as the interaction variable capturing heterogeneity of the LATE. Naturally, since both the HC and QoG indicators are measured relative to the EU average, the main effect of Objective 1 treatment is almost the same in both tables and is in line with the estimates in Becker, Egger, and von Ehrlich (2010) which only looked at the LATE of Objective 1 treatment. As for the role of quality of government, it turns out

[12] In all cases, we include a polynomial function of HC that is once uninteracted and once interacted with the treatment dummy in order to be able to distinguish between a role of human capital for growth as such ('main effect') and its role for the HLATE. All results are also robust to the introduction of interaction terms between (polynomials of) the forcing variable and (polynomials of) the measures of absorptive capacity.

that regions with better quality of government have a larger treatment effect, as we would expect. Taking the pooled OLS specification with a 5th-order polynomial function of the forcing variable and a linear function of QoG as the benchmark, a one standard deviation of quality of government renders the treatment effect about 41% higher compared to the average level of QoG.

Table 4 goes one step further and analyzes how the LATE varies along both the HC and QoG dimensions. We look at linear interaction terms in HC and QoG and in HC·QoG. The main interaction effect of quality of government (Object1·QoG) becomes statistically insignificant, but the heterogeneity along the HC dimension remains strong. Furthermore, in the fixed effects regressions, also the Object1·HC·QoG term is significantly positive, suggesting that quality of government translates into a higher treatment effect in the presence of higher human capital levels in the recipient region.

The relevant nonparametric estimates of LATE in Tables 5 and 6 are very close to their parametric counterparts in Tables 2 and 3. Notice that bandwidth choice has an impact on the estimated LATE, referred to as $\widehat{LATE}$. However, the difference in the point estimates across columns is moderate. If one chooses too small a bandwidth, variability increases a lot and $\widehat{LATE}$ can not be estimated precisely enough to reject the null hypothesis of a zero impact of Objective 1 on per-capita income growth. However, according to the cross-validation procedure suggested by Ludwig and Miller (2007), one would choose an optimal bandwidth of 0.2 for the treatment stage and one of 0.3 for the outcome stage with the data at hand. When using such a bandwidth, $\widehat{LATE} \approx 0.021$ which is significantly different from zero at the 1% level.

Notice that Tables 5 and 6 do not provide the information we are most interested in, namely whether and how LATE varies with absorptive capacity. Likewise, Tables 2 and 3 do not display the treatment effects for different levels of absorptive capacity directly. Therefore, we choose a graphical illustration of $\widehat{HLATE}$ and its 90% confidence bounds. The findings are portrayed in two panels in Figures 4 and 5 for the human capital (HC) and the quality of government (QoG) variables, respectively. The panels on the left of the two figures represent parametric estimates while the ones on the right represent their nonparametric counterparts.

The parametric results are based upon the coefficients of the cubic specification of the forcing variable and a linear term in HC and QoG, while the nonparametric estimates are based on the optimal bandwidth according to the Ludwig and Miller (2007) criterion in Tables 5 and 6. The four graphs represent estimates of the HLATE at the threshold of the forcing variable of Objective 1 treatment. Under the maintained assumptions, they are consistent estimates of the (fuzzy) discontinuity displayed in the outcome plot in Figure 3.

– Figure 4 and 5 –

In line with the results in the above Tables, $\widehat{HLATE}$ is monotonic in absorptive capacity for both the parametric and the nonparametric specification. The graphs show a monotonic increase of the HLATE with human capital. Not surprisingly, the confidence intervals are wider for the nonparametric estimates than for their parametric counterparts. Similarly, the HLATE with respect to quality of government, again shows a monotonic relationship: higher quality of government is associated with a larger Objective 1 treatment effect.

Finally, Figure 6 shows how human capital and quality of government interact, leading to larger treatment effects in the HC and QoG dimensions. The figure is based on a specification that includes a 3rd-order polynomial of per-capita GDP and linear terms of HC and QoG. The light dots mark areas where the HLATE is insignificant: light blue dots refer to negative point estimates and light red ones to positive point estimates. The dark red dots mark areas where the HLATE is positive and significantly different from zero. According to these estimates, for a positive and significant HLATE the human capital endowment as well as the quality of government have to exceed certain critical levels. For regions below those levels, Objective 1 transfers can not be rejected to be a wash. Once the critical values are passed – i.e., an observation lies within the dark red area – transfers are more effective with higher levels of both human capital and quality of government. The fact that the HLATE is a continuous function of measures of absorptive capacity allows us to exploit that functional form even further. For instance, we can gain insights into the geographic location of areas where absorptive capacity was insufficient to generate additional growth from EU funds.

– Figure 6 – and Table 7

Table 7 provides information on the percentage of Objective 1 regions among the EU member countries that received Objective 1 funds and had at the same time sufficiently high levels of human capital and quality of government for realizing positive treatment effects that are significantly different from zero. These figures are derived from assigning the recipient regions within the respective countries to the surface illustrated in Figure 6. The table contains three columns with numbers: the first one of them provides the percentage of a country's regions with a positive average treatment effect among all of its Objective 1 regions; the second and third column only consider regions with a real per-capita income in the 60-90% and 65-85% brackets of the forcing variable which determines Objective 1 transfer eligibility at a level of the forcing variable of less than 75%. Of course, the denominator underlying the respective percentages is smallest in the third column where the window in forcing-variable space is smallest and largest in the first column where all Objective 1 regions are covered.

The percentage in Table 7 is zero whenever a country has a positive number of Objective 1 regions within the specified window, but none of them receives a positive HLATE which is significantly different from zero according to Figure 6. The percentage is 100 whenever a country has a positive number of Objective 1 regions within the specified window, and all of them receive a positive HLATE which is significantly different from zero according to Figure 6. The entry in Table 7 is "–" in case a country does not have any Objective 1 regions within the specified window. All other entries are in the support region of $(0, 100)$. In general, we would consider the estimates underlying Figure 6 to be better suited with smaller windows around the eligibility threshold. On average, the estimated treatment effects appear to be positive and significant with greater probability for Objective 1 regions in the incumbent countries of the European Union. The zeros for Belgium, Finland, and Ireland and the 100s for Estonia and Malta are exceptions which accrue to low values of either the human capital endowments (HC) or the quality of government (QoG) dimensions and to high values in either dimension, respectively.

### 3.3 Policy considerations

The results provoke a number of alternative policy conclusions. Figure 6 suggests that significantly positive effects of Objective 1 transfers are only to be had with sufficiently high levels of human capital endowments (HC) and quality of government (QoG). This is the case for only 107 out of 227 recipients (when considering all observations as in the first column of Table 7). Hence, one could say that the European Commission could save money by voiding Objective 1 transfers to about 53% percent of the recipients. For the most part, those regions belong in the group of least-developed regions within the EU. By the same token, the Commission could stimulate further growth by reallocating transfers from 53% of regions without any positive significant response to the other ones. Either measure would counteract the very purpose of the programme, though, which is reducing per-capita income gaps and stimulating convergence from the tails towards the average within the European Union.

An alternative proposal could be to use funds at the Structural Programme in a more discretionary fashion than at present and to target human capital formation and political as well as administrative institutions (quality of government) in regions which are eligible for transfers. According to our findings, such an approach would be largely complementary to other means of redistribution. In terms of labels of initiatives at the level of the European Commission, this could be seen as an argument in favor of strengthening and broadening efforts around measures taken under the auspices of the *Regional Competitiveness and Employment Objective* (formerly Objective 2) rather than the *Convergence Objective* (formerly Objective 1). Of course, significant changes in the response to transfers induced by such measures should not be expected to happen in the very short run. Both the formation of human capital as well as institutional change take time – most likely about one generation rather than a small number of years. But the returns on those investments in terms of growth effects might be higher than ones on infrastructure and other types of real investments to regions that lack complementary factors such as skilled workers or high-quality institutions to realize the expected growth stimuli.

On a broader scale, the notion that fiscal policy induces heterogeneous responses across recipients is consistent with recent findings in the macro literature on fiscal multipliers. For instance, Auerbach and Gorodnichenko (2010, 2011) provide evidence of state-dependent effects of fiscal multipliers. While there is evidence of a positive effect of fiscal multipliers over the longer run (see Gemmell, Kneller, and Sanz, 2011; Ramey, 2011), Auerbach and Gorodnichenko's (2010, 2011) findings suggest that effects can vary significantly over the business cycle. There is also work on the heterogeneity of treatment effects in the cross section. Shoah (2011) uses variation in portfolio returns of defined-benefit pension plans across US states – for which the state governments bear the investment risk – to identify the effect of state government spending on in-state income and employment. He detects heterogeneity in that the effect is stronger in non-tradable industries and when economic slack is high. Suárez Serrato and Wingender (2011) exploit US county-level variation in receipt of US federal grants that depend on local population levels to estimate local fiscal multipliers. They show that there is heterogeneity of the impacts of government spending and that there is a higher impact in low-growth areas. The latter is consistent with the finding that transfers are more effective in regions of the EU with higher levels of absorptive capacity than elsewhere.

# 4 Discussion and conclusions

This paper studies the role of absorptive capacity of regions in translating transfers into economic growth. In particular, we study the importance of absorptive capacity for the treatment effect triggered by regional transfers under the auspices of Objective 1 under the Structural Funds Programme of the European Commission. A region's initial GDP per capita relative to the EU average determines eligibility of NUTS regions in the European Union to receive transfers out of the Structural Funds. Regions whose initial GDP per capita is less than 75% of the EU average are eligible to receive Objective 1 funds. Econometrically, this gives rise to a regression discontinuity design (RDD). To the extent that a region's absorptive capacity systematically influences how efficiently it uses transfers received, we expect heterogeneity in local average treatment effects (LATE) which varies with the recipient region's absorptive capacity. We derive a heterogeneous LATE (HLATE) estimator for the general scenario with multiple thresholds and various interaction variables that affect the treatment effect's magnitude, and we allow for a fuzzy treatment assignment mechanism. In a Monte Carlo simulation, we study the performance of parametric and nonparametric identification strategies for such an heterogeneous treatment effect and show that both approaches yield consistent estimators.

In our empirical illustration, we show that the heterogeneity of recipient regions with respect to their absorptive capacity matters considerably. Both measures of a region's absorptive capacity, the human capital endowment of the workforce and quality of government, show similar patterns. While the treatment effect is insignificant for regions with a very low level of absorptive capacity it exceeds the average treatment effect for regions with above-average absorptive capacity.

Our findings are complementary to recent work on the heterogeneous responses to fiscal stimuli in macroeconomics in the sense that fiscal multipliers may differ dramatically across recipients. We estimate positive responses to stimuli (transfers) to be higher for recipients with higher levels of absorptive capacity measured as an above-average endowment of human capital and an above average level of quality of government.

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# Appendix A. Deriving the HLATE

We aim at proving

$$HLATE(\mathbf{x_0}, \mathbf{z_i}) = \lim_{\mathbf{\Delta}\to\mathbf{0}} \frac{E[y_i|\mathbf{0} < \widetilde{\mathbf{x}}_\mathbf{i} < \mathbf{\Delta}, \mathbf{z_i}] - E[y_i| - \mathbf{\Delta} < \widetilde{\mathbf{x}}_\mathbf{i} < \mathbf{0}, \mathbf{z_i}]}{E[T_i = 1|\mathbf{0} < \widetilde{\mathbf{x}}_\mathbf{i} < \mathbf{\Delta}, \mathbf{z_i}] - E[T_i = 1| - \mathbf{\Delta} < \widetilde{\mathbf{x}}_\mathbf{i} < \mathbf{0}, \mathbf{z_i}]}$$

The outcome difference of observations at the threshold is

$$\begin{aligned} E[y_i|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}] - E[y_i|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}] = \\ E[T_i\beta|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}] - E[T_i\beta|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}] \\ +E[\mathbf{z_i}\beta|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}] - E[\mathbf{z_i}\beta|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}] \\ +E[\alpha_i|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}] - E[\alpha_i|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}] \end{aligned}$$

We assume that $E[\alpha_i|\mathbf{x_i} = \mathbf{x}]$ is continuous at $\mathbf{x_0}$ such that the last two terms in the above equation cancel each other out as $\mathbf{\Delta}$ moves towards zero. Assuming conditional independence between $T_i$ and $\beta$ as well as between $\mathbf{z_i}$ and $\beta$ yields

$$\begin{aligned} &E[y_i|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}] - E[y_i|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}] = \\ &E[\beta|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}]E[T_i|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}] + E[\beta|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}]E[\mathbf{z_i}|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{\Delta}, \mathbf{z_i}] \\ -&E[\beta|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}]E[T_i|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}] - E[\beta|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}]E[\mathbf{z_i}|\widetilde{\mathbf{x}}_\mathbf{i} = -\mathbf{\Delta}, \mathbf{z_i}] \end{aligned}$$

Note that conditional independence requires that no selection into treatment on the basis of the expected effect occurs. Assuming that $E[\beta|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{0}]$ is continuous at $\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{0}$ then delivers

$$\lim_{\boldsymbol{\Delta}\to 0} E[y_i|\widetilde{\mathbf{x}}_\mathbf{i} = \boldsymbol{\Delta}, \mathbf{z}_\mathbf{i}] - \lim_{\boldsymbol{\Delta}\to 0} E[y_i|\widetilde{\mathbf{x}}_\mathbf{i} = -\boldsymbol{\Delta}, \mathbf{z}_\mathbf{i}] = \\ E[\beta|\widetilde{\mathbf{x}}_\mathbf{i} = \mathbf{0}, \mathbf{z}_\mathbf{i}] \left( \lim_{\boldsymbol{\Delta}\to 0} E[T_i|\widetilde{\mathbf{x}}_\mathbf{i} = \boldsymbol{\Delta}, \mathbf{z}_\mathbf{i}] - \lim_{\boldsymbol{\Delta}\to 0} E[T_i|\widetilde{\mathbf{x}}_\mathbf{i} = -\boldsymbol{\Delta}, \mathbf{z}_\mathbf{i}] \right)$$

which can easily be reformulated to obtain $HLATE(\mathbf{z}_\mathbf{i})$ from above.

# Appendix B. Standard errors of the HLATE

Under the maintained assumptions in this paper and Assumptions (i)-(vii) in Hahn, Todd, and van der Klaauw (2001), the estimate $\widehat{HLATE}(\mathbf{x}_\mathbf{0}, \mathbf{z}_\mathbf{i})$ is distributed as

$$n^{2/5}[\widehat{HLATE}(\mathbf{x}_\mathbf{0}, \mathbf{z}_\mathbf{i}) - HLATE(\mathbf{x}_\mathbf{0}, \mathbf{z}_\mathbf{i})] \to \mathfrak{N}\left[\mu_{HLATE}(\mathbf{x}_\mathbf{0}, \mathbf{z}_\mathbf{i}), \Omega_{HLATE}(\mathbf{x}_\mathbf{0}, \mathbf{z}_\mathbf{i})\right] \tag{11}$$

where $\mu_{HLATE}(\mathbf{x}_\mathbf{0}, \mathbf{z}_\mathbf{i})$ approaches zero as $\boldsymbol{\Delta}$ in (9) approaches zero. $\Omega_{HLATE}(\mathbf{x}_\mathbf{0}, \mathbf{z}_\mathbf{i})$ in (11) is then defined as in Hahn, Todd, and van der Klaauw (2001) conditional on $\mathbf{z}_\mathbf{i}$.

# Appendix C. Monte Carlo study

## Appendix C.1. Simulation design

In the following we examine the performance of parametric and nonparametric estimators in identifying the HLATE. We consider sharp and fuzzy designs for the HLATE and scenarios where the treatment depends on one (1-way threshold) versus two forcing variables (2-way threshold). In the application in Section 3 only one forcing variable matters for treatment assignment, yet it is useful to consider a more general case other applications rely upon (see Egger and Wamser, 2011). For each case (sharp versus fuzzy and 1-way versus 2-way), let us consider $3 \cdot 2$ experiments: a Sharp RDD, a Fuzzy 1 RDD with a low degree of fuzziness, and a Fuzzy 2 RDD with a high degree of fuzziness about treatment assignment (see below); a standard deviation of the disturbances $\epsilon_i$ of $\sigma_\epsilon = 0.3$ versus $\sigma_\epsilon = 0.6$. In any case, $\epsilon_i$ is distributed as $\epsilon_i$ $i.i.d.N(0, \sigma_\epsilon)$.

We generate the data about $x_i$ and $z_i$ for observation $i = 1, \ldots, N$ based on a grid of $60 \cdot 60$ bins in $x$-$z$-space. In each dimension, bins take addresses (i.e., values of $x_i$ and $z_i$) between $-2.95$ and $2.95$ and have a size of 0.1. We, assume that each of the $60^2 = 3,600$ bins hosts 6 observations with identical values of $x_i$ and $z_i$ but an independent draw of $\epsilon_i$. Hence, there is a total number of $21,600$ observations available to the largest data-set possible. This aims at mimicking the empirical situation with RDDs where one allots data points into bins to generate averages of $x_i$ ($z_i$) and $y_i$ (see Angrist and Pischke, 2009; Lee and Lemieux, 2010). To illustrate the small sample performance of the nonparametric estimator of the HLATE and compare it with its parametric counterpart, we alternatively consider subsets of that data-set where consider sub-grids of $40 \cdot 40$ in the support region of $[-1.95, 1.95]$ in $x$-$z$-space with $40^2 \cdot 6 = 9,600$ observations and $20 \cdot 20$ in the support region of $[-0.95, 0.95]$ in $x$-$z$-space with $20^2 \cdot 6 = 2,400$ observations.

In each of the experiments, LATE corresponds to the average level of HLATE and is measured by the coefficient on the treatment dummy $T_i$, i.e., $\beta = 1$.

**1-way threshold**

With a 1-way threshold rule, the data generating processes can be described as follows.

Sharp RDD:

$$\begin{aligned} y_i =& 1 + T_i + .5T_i z_i + .5x_i + .5z_i + .1x_i^2 + .1z_i^2 + .3x_i z_i + \epsilon_i \\ & where\ T_i = 1(x_i \geq 0) \end{aligned}$$

Fuzzy 1 RDD:

$$\begin{aligned} y_i =& 1 + T_i + .5T_i z_i + .5x_i + .5z_i + .1x_i^2 + .1z_i^2 + .3x_i z_i + \epsilon_i \\ & where\ P(T_i = 1) = \begin{cases} 1 & \text{if } x_i > b \\ 11/12 & \text{if } 0 \leq x_i \leq b \\ 1/12 & \text{if } -b \leq x_i < 0 \\ 0 & \text{if } x_i < -b \end{cases} \end{aligned}$$

For the simulations, we chose $b = 0.45$ so that the probability of treatment mis-assignment is 1/12 in the support region of $[-0.45, 0.45]$ in $x$-space (i.e., in 5 bins to the left and in 5 bins to the right of the 1-way threshold). The maximum of observations in the mis-classification region are $10 \cdot 60 \cdot 6 = 3,600$, $10 \cdot 40 \cdot 6 = 2,400$, and $10 \cdot 20 \cdot 6 = 1,200$, depending on the chosen grid and sample size. Hence, 300, 200, and 100 observations, respectively, are expected to be misclassified. Note that the random process underlying the fuzzyness are drawn for each replication of the monte carlo study separately.

Fuzzy 2 RDD:

$$y_i = 1 + T_i + .5T_iz_i + .5x_i + .5z_i + .1x_i^2 + .1z_i^2 + .3x_iz_i + \epsilon_i$$

$$where\ P(T_i = 1) = \begin{cases} 1 & \text{if } x_i > b \\ 5/6 & \text{if } 0 \leq x_i \leq b \\ 1/6 & \text{if } -b \leq x_i < 0 \\ 0 & \text{if } x_i < -b \end{cases}$$

As in the Fuzzy 1 design, we chose $b = 0.45$ but we assumed the probability of treatment mis-assignment amounting to 1/6 in the support region of $[-0.45, 0.45]$ in $x$-space. Hence, depending on the chosen grid and sample size, 600, 400, and 200 observations, respectively, are expected to be misclassified in the Fuzzy 2 design.

The results for the Sharp RDD are illustrated in Figure 7 and the ones for the Fuzzy 1 and Fuzzy 2 RDDs are illustrated in Figure 8. In the 1-way experiments, the treatment is only determined by forcing the variable $x_i$ whereas the outcome is affected by $x_i$ and $z_i$. The heterogenous treatment effect appears in the outcome graphs as a wedge between the red (treated) and the blue (untreated) observations. The extent of heterogeneity of LATE is noticeable as the outcome shift between treated and non-treated observations disappears for low values of $z_i$. In the fuzzy experiments illustrated in Figure 8, the treatment probability (approximated by the fraction of treated observations) jumps at the threshold $x_0$ by about 0.85 and 0.65 in the Fuzzy 1 and Fuzzy 2 designs, respectively, which reflects the corresponding mis-classification probabilities of 1/12 and 1/6. With a fuzzy design, some of the red observations characterized by $x_i > x_0$ do *not* receive treatment while some of of the blue observations with $x_i < x_0$ *do* receive treatment. This fuzziness blurs the discontinuity in the outcome function and results in a smaller treatment wedge compared to the sharp design. According to equation (9), the treatment effect is measured by the ratio of the outcome wedge and the jump in the treatment probability.

– Figures 7 and 8 –

**2-way threshold**

With a 2-way threshold, both $x_i$ and $z_i$ serve as forcing variables and LATE also varies with $z_i$. With respect to $x_i$, we maintain the threshold value $x_0 = 0$ while now also $z_i$ has to exceed a level of $z_0 = -0.6$ in order to qualify for treatment. For (sharp) treatment assignment we require both rules to be fulfilled at the same time.[13] Distinguishing again between sharp and fuzzy scenarios we consider the following experiments in the 2-way threshold design:

[13] Recent work by Wong, Steiner and Cook (2010) considers multiple threshold rules but requires only one rule to be satisfied for treatment.

Sharp RDD:

$$\begin{aligned} y_i =& 1 + T_i + .5T_i z_i + .5x_i + .5z_i + .1x_i^2 + .1z_i^2 + .3x_i z_i + \epsilon_i \\ & \textit{where } T_i = 1(x_i \geq 0 \wedge z_i \geq -0.6) \end{aligned}$$

Fuzzy 1 RDD:

$$\begin{aligned} y_i =& 1 + T_i + .5T_i z_i + .5x_i + .5z_i + .1x_i^2 + .1z_i^2 + .3x_i z_i + \epsilon_i \\ & \textit{where } P(T_i = 1) = \begin{cases} 1 & \text{if } x_i > b \wedge z_i > -.6 + b \\ 11/12 & \text{if } 0 \leq x_i \leq b \wedge -0.6 - b \leq z_i \leq -.6 \\ 1/12 & \text{if } b \leq x_i < 0 \wedge -.6 \leq z_i \leq -.6 + b \\ 0 & \text{if } x_i < b \wedge z_i < -.6 + b \end{cases} \end{aligned}$$

As with a 1-way treatment threshold, we chose $b = 0.45$ and the probability of treatment mis-assignment is 1/12 in the chosen support region. However, now treatment mis-classification may vary with both $x_i$ and $z_i$. Therefore, we chose the support region to be bounded by $[-0.45, 0.45]$ in $x$-space and by $[-1.05, -0.15]$ in $z$-space. The maximum of observations in the mis-classification region are $10 \cdot 10 \cdot 6 = 600$, independent of the chosen grid and sample size. Hence, 50 observations are expected to be misclassified in any one of the fuzzy design experiments.

Fuzzy 2 RDD:

$$\begin{aligned} y_i =& 1 + T_i + .5T_i z_i + .5x_i + .5z_i + .1x_i^2 + .1z_i^2 + .3x_i z_i + \epsilon_i \\ & \textit{where } P(T_i = 1) = \begin{cases} 1 & \text{if } x_i > b \wedge z_i > -.6 + b \\ 7/8 & \text{if } 0 \leq x_i \leq b \wedge -0.6 - b \leq z_i \leq -.6 \\ 1/8 & \text{if } b \leq x_i < 0 \wedge -.6 \leq z_i \leq -.6 + b \\ 0 & \text{if } x_i < b \wedge z_i < -.6 + b \end{cases} \end{aligned}$$

As in the 2-way threshold Fuzzy 1 design, we chose $b = 0.45$ but we assumed the probability of treatment mis-assignment amounting to 1/6 in the support region of $[-0.45, 0.45]$ in $x$-space and $[-1.05, -0.15]$ in $z$-space. Hence, 100 observations are generally expected to be misclassified in the 2-way Fuzzy 2 design. The 2-way Sharp RDD is illustrated in Figure 9 and the corresponding Fuzzy 1 and Fuzzy 2 RDDs are illustrates in Figure 10.

– Figures 9 and 10 –

Notice that, apart from the different design in general, the 2-way (H)LATE estimates are based on a smaller number of cells and observations at the the treatment thresholds. The latter should not have any bearing for the bias but it comes at a loss of precision of the estimates in comparison to the 1-way threshold results.

## 4.1 Appendix C.2. Results

The simulation results for the local average treatment effect (LATE; at $x, z = 0$) are presented in Table 8 for a 1-way threshold design (and in Table 9 for a 2-way threshold design). Those for the heterogeneous local average treatment effect (HLATE; at $x = 0$ across all $z$) are presented graphically in Figure A.5. Remember that LATE in the sense of the average HLATE corresponds to the coefficient on the treatment dummy $T_i$, i.e., $\beta = 1$. The bias is measured as a deviation of the estimate $\hat{\beta}$ from the true parameter $\beta = 1$ in percent.

Note that, for the parametric estimates, we use the true functional form, i.e., that of the data-generating process. (Our interest is not in simulating the effect of mis-specification of the control function, but in illustrating the small sample performance of nonparametric relative to parametric estimates of the HLATE.)

The findings can be summarized as follows. First, the estimates of both the nonparametric and the parametric estimates of LATE ($\beta$) appear to have a small bias across all experiments considered in the Monte Carlo analysis. In every one of the experiments is the bias of LATE smaller than one percent in absolute value independent of sample size of whether we consider a sharp or a fuzzy RDD (see the panels at the top of Tables 8 and 9). All else equal, the mean squared error tends to be smallest with a sharp design, a smaller value of $\sigma_\epsilon$, a larger bandwidth considered, parametric rather than nonparametric estimates, and a 1-way instead of a 2-way threshold design. None of that is surprising, since fuzzy designs add noise to the estimation problem by involving a projection of the endogenous treatment status in a first stage; a larger value of $\sigma_\epsilon$ involves more noise at the level of the outcome equation; a smaller bandwidth considered is associated with a smaller number of observations we estimate the HLATE from, thus reducing precision; more flexible nonparametric estimates involve a loss of precision, if the true functional form of the relationship between the forcing variable ($x$) and also of the variable which interacts with treatment status ($z$) is a parametric polynomial; and the 2-way threshold design requires more parameters to be estimates – in our case, from a smaller number of observations at which the threshold is observed – which leads to efficiency losses.

– Tables 8 and 9

These insights about LATE also carry over to the estimation of HLATE in Figure 8. Quite obviously, the point estimates are virtually indistinguishable from the true values, but the estimated confidence intervals are smaller for the parametric estimates (which assumes the true functional form) than for the more flexible, local-linear-regression-based nonparametric estimates. Finally, the estimates for the 2-way threshold regressions in Figure 9 have somewhat larger confidence intervals than their counterparts for the 1-way thresholds.

Hence, we may conclude that both the nonparametric and the parametric estimates work well in small to moderately large samples. In empirical circumstances where parametric approximations of unknown functional forms will not work as well as in the Monte Carlo study, where the parametric estimates assumed the correct form of the control function, we expect nonparametric estimates to work quite well. In any case, HLATE can be inferred with very small bias from both nonparametric and parametric control function, irrespective of whether a sharp or a fuzzy design is being considered.

– Figures 11 and 12 –

## 4.2 Appendix D. Frequency of Observations

– Figure 13 –

# Tables and Figures

Table 1: Descriptive Statistics

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| GDP per capita growth | .042 | .018 | -.008 | .131 |
| Objective 1 | .306 | .461 | 0 | 1 |
| Avg. GDP per capita in threshold years | 12,927.270 | 4,562.467 | 3,343.816 | 37,835.190 |
| Avg. GDP per capita in threshold years/EU avg. | 1.189 | .414 | .229 | 3.104 |
| Human capital (HC) | 0 | .148 | -.403 | .315 |
| Quality of government (QoG) | 0 | .825 | -2.699 | 1.244 |

*Notes*: Units of observation are EU NUTS2 regions. GDP data are from Cambridge Econometrics; information about Objective 1 treatment is available directly from the European Commission, from various Council Regulations, in particular the Regulations numbered 2052/88, 2082/93, and 502/1999, and in editions of the Official Journal (see also Becker, Egger, and von Ehrlich, 2010); the human capital (HC) variable measures the share of the workforce with at least upper-secondary education (ISCED categories 3 to 6); the quality of government (QoG) index comes from Charron and Lapuente (2011); both the HC and QoG variables are normalized to zero, by detracting the EU average; see the main text for more detail.
We miss information on the four French overseas-départements and the two autonomous Portuguese regions Madeira and Azores for all three periods. For the Dutch region Flevoland we miss information for the first period only. Regarding the East-German NUTS2 regions we calculated GDP per capita growth for the years 1989 and 1990 using information from the GDR's statistic yearbook. The EU QoG index is not available for the Spanish region Ceuta and Melilla.

Table 2: Objective 1 Treatment and Human Capital (parametric identification)

| | 3rd-order polynomial | | 4th-order polynomial | | 5th-order polynomial | |
|---|---|---|---|---|---|---|
| | Pooled OLS | FE | Pooled OLS | FE | Pooled OLS | FE |
| **linear HC** | (1) | (2) | (3) | (4) | (5) | (6) |
| Object1 | .010 | .012 | .007 | .008 | .006 | .011 |
| | (.003)$^{***}$ | (.003)$^{***}$ | (.003)$^{**}$ | (.004)$^{**}$ | (.004)$\sharp$ | (.004)$^{***}$ |
| Object1×HC | .039 | .039 | .045 | .044 | .046 | .044 |
| | (.009)$^{***}$ | (.009)$^{***}$ | (.009)$^{***}$ | (.009)$^{***}$ | (.009)$^{***}$ | (.009)$^{***}$ |
| HC | .011 | .007 | .008 | .003 | .007 | .002 |
| | (.008) | (.007) | (.008) | (.007) | (.008) | (.007) |
| Const. | .040 | .017 | .041 | .014 | .040 | .010 |
| | (.001)$^{***}$ | (.009)$^{**}$ | (.002)$^{***}$ | (.010) | (.002)$^{***}$ | (.011) |
| Obs. | 674 | 674 | 674 | 674 | 674 | 674 |
| $R^2$ | .363 | .38 | .369 | .402 | .369 | .408 |
| **quadratic HC** | (1) | (2) | (3) | (4) | (5) | (6) |
| Object1 | .013 | .016 | .009 | .009 | .009 | .010 |
| | (.003)$^{***}$ | (.004)$^{***}$ | (.004)$^{**}$ | (.004)$^{**}$ | (.004)$^{*}$ | (.004)$^{***}$ |
| Object1×HC | .051 | .055 | .048 | .051 | .048 | .049 |
| | (.011)$^{***}$ | (.011)$^{***}$ | (.011)$^{***}$ | (.011)$^{***}$ | (.010)$^{***}$ | (.010)$^{***}$ |
| Object1× $HC^2$ | .184 | .325 | .101 | .227 | .075 | .182 |
| | (.130) | (.137)$^{**}$ | (.139) | (.138)$^{*}$ | (.132) | (.129) |
| HC | .005 | -.004 | .007 | -.001 | .007 | -.0007 |
| | (.009) | (.009) | (.009) | (.009) | (.009) | (.008) |
| $HC^2$ | -.151 | -.258 | -.073 | -.164 | -.049 | -.126 |
| | (.130) | (.130)$^{**}$ | (.135) | (.129) | (.129) | (.122) |
| Const. | .039 | .004 | .040 | .007 | .039 | .005 |
| | (.001)$^{***}$ | (.011) | (.002)$^{***}$ | (.012) | (.002)$^{***}$ | (.012) |
| Obs. | 674 | 674 | 674 | 674 | 674 | 674 |
| $R^2$ | .337 | .338 | .36 | .389 | .363 | .4 |
| **cubic HC** | (1) | (2) | (3) | (4) | (5) | (6) |
| Object1 | .015 | .014 | .012 | .009 | .012 | .010 |
| | (.003)$^{***}$ | (.004)$^{***}$ | (.004)$^{***}$ | (.004)$^{**}$ | (.005)$^{***}$ | (.004)$^{**}$ |
| Object1×HC | .113 | .098 | .113 | .092 | .112 | .087 |
| | (.021)$^{***}$ | (.022)$^{***}$ | (.021)$^{***}$ | (.023)$^{***}$ | (.021)$^{***}$ | (.023)$^{***}$ |
| Object1× $HC^2$ | .157 | .306 | .116 | .268 | .077 | .213 |
| | (.085)$^{*}$ | (.106)$^{***}$ | (.082) | (.100)$^{***}$ | (.081) | (.098)$^{**}$ |
| Object1× $HC^3$ | -2.190 | -1.842 | -2.157 | -1.706 | -2.076 | -1.570 |
| | (.666)$^{***}$ | (.664)$^{***}$ | (.654)$^{***}$ | (.661)$^{***}$ | (.644)$^{***}$ | (.673)$^{**}$ |
| HC | -.046 | -.050 | -.046 | -.048 | -.044 | -.043 |
| | (.016)$^{***}$ | (.016)$^{***}$ | (.016)$^{***}$ | (.016)$^{***}$ | (.016)$^{***}$ | (.016)$^{***}$ |
| $HC^2$ | -.168 | -.248 | -.131 | -.200 | -.095 | -.153 |
| | (.074)$^{**}$ | (.084)$^{***}$ | (.067)$^{*}$ | (.075)$^{***}$ | (.067) | (.071)$^{**}$ |
| $HC^3$ | 1.980 | 1.854 | 1.948 | 1.772 | 1.866 | 1.632 |
| | (.644)$^{***}$ | (.633)$^{***}$ | (.623)$^{***}$ | (.607)$^{***}$ | (.612)$^{***}$ | (.617)$^{***}$ |
| Const. | .038 | .010 | .038 | .011 | .037 | .010 |
| | (.001)$^{***}$ | (.009) | (.002)$^{***}$ | (.010) | (.002)$^{***}$ | (.011) |
| Obs. | 674 | 674 | 674 | 674 | 674 | 674 |
| $R^2$ | .356 | .366 | .371 | .401 | .376 | .413 |

*Notes*: $^{***}$, $^{**}$, $^{*}$, $^{\sharp}$ denote significance at the 1, 5, 10, and 15% level, respectively. Standard errors are clustered at the NUTS2 level. First-stage regressions are probit models. The polynomial functions are allowed to have different parameters to the left and the right of the threshold. The human capital variable (HC) is time-invariant. The sample consists of the EU12 NUTS2 regions for the first period, the EU15 NUTS2 regions for the second period, and the EU25 NUTS2 regions for the third programming period. We miss information on the four French overseas-départements and the two autonomous Portuguese regions Madeira and Azores for all three periods. For the Dutch region Flevoland we miss information for the first period only. Regarding the East-German NUTS2 regions, we calculated GDP per capita growth for the years 1989 and 1990 using information from the GDR's statistic yearbook.

Table 3: Objective 1 Treatment and Quality of Government (parametric identification)

| | 3rd-order polynomial | | 4th-order polynomial | | 5th-order polynomial | |
|---|---|---|---|---|---|---|
| | Pooled OLS | FE | Pooled OLS | FE | Pooled OLS | FE |
| **linear QoG** | (1) | (2) | (3) | (4) | (5) | (6) |
| Object1 | .007 | .012 | .008 | .010 | .010 | .016 |
| | (.004)* | (.004)*** | (.004)* | (.004)*** | (.004)*** | (.004)*** |
| Object1×QoG | .005 | .005 | .005 | .006 | .005 | .006 |
| | (.002)** | (.002)*** | (.002)** | (.002)*** | (.002)*** | (.002)*** |
| QoG | .002 | .002 | .002 | .001 | .001 | .001 |
| | (.002) | (.001) | (.002) | (.001) | (.002) | (.001) |
| Const. | .039 | -.003 | .039 | -.007 | .038 | -.010 |
| | (.002)*** | (.009) | (.002)*** | (.010) | (.002)*** | (.012) |
| Obs. | 668 | 668 | 668 | 668 | 668 | 668 |
| $R^2$ | .315 | .356 | .314 | .374 | .312 | .376 |
| **quadratic QoG** | (1) | (2) | (3) | (4) | (5) | (6) |
| Object1 | .005 | .007 | .004 | .004 | .006 | .009 |
| | (.004)♯ | (.003)** | (.004) | (.004) | (.003)* | (.003)*** |
| Object1×QoG | .006 | .009 | .006 | .009 | .007 | .011 |
| | (.003)* | (.003)*** | (.003)* | (.003)*** | (.003)** | (.003)*** |
| Object1×QoG$^2$ | -.005 | -.0006 | -.005 | -.0009 | -.004 | .0005 |
| | (.002)* | (.002) | (.003)* | (.002) | (.002)* | (.002) |
| QoG | .0007 | .0005 | .0005 | .0003 | .0005 | .00002 |
| | (.002) | (.002) | (.002) | (.001) | (.002) | (.001) |
| QoG$^2$ | .005 | .003 | .005 | .003 | .005 | .002 |
| | (.002)** | (.002) | (.002)** | (.002)* | (.002)** | (.001) |
| Const. | .039 | -.0007 | .040 | -.006 | .040 | -.009 |
| | (.001)*** | (.008) | (.002)*** | (.010) | (.002)*** | (.011) |
| Obs. | 668 | 668 | 668 | 668 | 668 | 668 |
| $R^2$ | .321 | .365 | .321 | .382 | .322 | .391 |
| **cubic QoG** | (1) | (2) | (3) | (4) | (5) | (6) |
| Object1 | .004 | .006 | .003 | .003 | .005 | .008 |
| | (.004) | (.004)♯ | (.004) | (.004) | (.004) | (.004)** |
| Object1×QoG | .008 | .012 | .009 | .012 | .009 | .013 |
| | (.004)** | (.004)*** | (.004)** | (.003)*** | (.003)*** | (.003)*** |
| Object1×QoG$^2$ | -.003 | .001 | -.003 | .001 | -.003 | .002 |
| | (.004) | (.004) | (.004) | (.004) | (.004) | (.004) |
| Object1×QoG$^3$ | -.003 | -.002 | -.002 | -.001 | -.002 | -.002 |
| | (.002) | (.002) | (.002) | (.002) | (.002) | (.002) |
| QoG | -.002 | -.002 | -.002 | -.002 | -.002 | -.002 |
| | (.002) | (.002) | (.002) | (.002) | (.002) | (.002) |
| QoG$^2$ | .005 | .002 | .005 | .003 | .005 | .002 |
| | (.002)** | (.002) | (.002)** | (.001)** | (.002)** | (.001)* |
| QoG$^3$ | .003 | .003 | .003 | .002 | .003 | .002 |
| | (.002) | (.002)* | (.002) | (.001) | (.002) | (.001) |
| Const. | .040 | -.0005 | .040 | -.005 | .040 | -.009 |
| | (.001)*** | (.008) | (.002)*** | (.010) | (.002)*** | (.011) |
| Obs. | 668 | 668 | 668 | 668 | 668 | 668 |
| $R^2$ | .323 | .365 | .323 | .382 | .324 | .391 |

*Notes*: ***, **, *, ♯ denote significance at the 1, 5, 10, and 15% level, respectively. Standard errors are clustered at the NUTS2 level. First-stage regressions are probit models. The polynomial functions are allowed to have different parameters to the left and the right of the threshold. The quality of government variable (QoG) is time-invariant and refers to the EU QoG index by Charron and Lapuente (2011). The sample consists of the EU12 NUTS2 regions for the first period, the EU15 NUTS2 regions for the second period, and the EU25 NUTS2 regions for the third programming period. We miss information on the four French overseas-départements and the two autonomous Portuguese regions Madeira and Azores for all three periods. For the Dutch region Flevoland we miss information for the first period only. Regarding the East-German NUTS2 regions, we calculated GDP per capita growth for the years 1989 and 1990 using information from the GDR's statistic yearbook.

Table 4: Objective 1 Treatment, Human Capital, and Quality of Government

| | 3rd-order polynomial | | 4th-order polynomial | |
|---|---|---|---|---|
| | Pooled OLS | FE | Pooled OLS | FE |
| Object1 | .009<br>(.003)** | .009<br>(.004)** | .009<br>(.004)** | .011<br>(.004)*** |
| Object1×QoG | -.0004<br>(.003) | .001<br>(.003) | -.0005<br>(.003) | .002<br>(.003) |
| Object1×HC | .043<br>(.014)*** | .044<br>(.013)*** | .043<br>(.014)*** | .041<br>(.012)*** |
| Object1×QoG×HC | .023<br>(.024) | .043<br>(.023)* | .022<br>(.024) | .045<br>(.023)** |
| QoG | .0003<br>(.002) | - | .0004<br>(.002) | - |
| HC | .006<br>(.012) | - | .006<br>(.012) | - |
| QoG×HC | -.042<br>(.023)* | - | -.042<br>(.023)* | - |
| Const. | .040<br>(.002)*** | .012<br>(.011) | .039<br>(.003)*** | .008<br>(.012) |
| Obs. | 668 | 668 | 668 | 668 |
| $R^2$ | .387 | .413 | .387 | .419 |

*Notes*: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are clustered at the NUTS2 level. First-stage regressions are probit models. The polynomial functions are allowed to have different parameters to the left and the right of the threshold. The human capital variable (HC) as well as the quality of government variable (QoG) are time-invariant. The sample consists of the EU12 NUTS2 regions for the first period, the EU15 NUTS2 regions for the second period, and the EU25 NUTS2 regions for the third programming period. We miss information on the four French overseas-départements and the two autonomous Portuguese regions Madeira and Azores for all three periods. For the Dutch region Flevoland we miss information for the first period only. Regarding the East-German NUTS2 regions, we calculated GDP per capita growth for the years 1989 and 1990 using information from the GDR's statistic yearbook.

Table 5: Objective 1 Treatment and Human Capital (nonparametric identification)

| Bandwidth: | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | Total | Optimal |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| LATE | -.0042 | .0178 | .0154** | .0146*** | .0168*** | .0166*** | .0207** |
| Std.err. | .1099 | .0171 | .0066 | .0049 | .0042 | .0036 | .0102 |

*Notes*: ***, **, *, ♯ denote statistical significance at the 1%, 5%, 10%, and 15% level, respectively. The nonparametric estimates are derived from multivariate local linear regressions with uniform kernel. The standard errors are calculated according to a plug-in procedure which was introduced by Imbens and Lemieux (2008). The average treatment effects in the first six columns refer to estimates with identical bandwidth for the respective conditional expectations of treatment and outcome. In the first five columns the bandwidth is expressed as the ratio of the average EU per-capita GDP (i.e., 0.1 indicates a bandwidth of 10% of average EU per-capita GDP). The sixth column uses the maximum bandwidth while the seventh column employs the optimal bandwidth according to the cross-validation procedure introduced by Ludwig and Miller (2007). We apply the cross-validation procedure to the conditional expectations of treatment and outcome separately which yields an optimal bandwidth of 0.2 for the treatment stage and 0.3 for the outcome stage.

Table 6: OBJECTIVE 1 TREATMENT AND QUALITY OF GOVERNMENT (NONPARAMETRIC IDENTIFICATION)

| Bandwidth: | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | Total | Optimal |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| LATE | -0.0080 | 0.0120 | 0.0078 | 0.0069 | 0.0107** | 0.0114 *** | 0.0105 |
| Std.err. | 0.1238 | 0.0163 | 0.0071 | 0.0053 | 0.0045 | 0.0038 | 0.0098 |

*Notes*: ***, **, *, ♯ denote statistical significance at the 1%, 5%, 10%, and 15% level, respectively. The nonparametric estimates are derived from multivariate local linear regressions with uniform kernel. The standard errors are calculated according to a plug-in procedure which was introduced by Imbens and Lemieux (2008). The average treatment effects in the first six columns refer to estimates with identical bandwidth for the respective conditional expectations of treatment and outcome. In the first five columns the bandwidth is expressed as the ratio of the average EU per-capita GDP (i.e., 0.1 indicates a bandwidth of 10% of average EU per-capita GDP). The sixth column uses the maximum bandwidth while the seventh column employs the optimal bandwidth according to the cross-validation procedure introduced by Ludwig and Miller (2007). We apply the cross-validation procedure to the conditional expectations of treatment and outcome separately which yields an optimal bandwidth of 0.2 for the treatment stage and 0.3 for the outcome stage.

Table 7: PERCENTAGE OF OBJECTIVE 1 REGIONS WITH SIGNIFICANT POSITIVE HLATE PER COUNTRY

| | Support region of forcing variable around 75%-threshold | | |
|---|---|---|---|
| Country | Total | 60-90% interval | 65-85% interval |
| Austria | 100 | 100 | 100 |
| Belgium | 0 | 0 | 0 |
| Czech Republic | 29 | - | - |
| Germany | 100 | 74 | 100 |
| Estonia | 100 | 100 | 100 |
| Spain | 38 | 23 | 29 |
| Finland | 0 | 0 | 0 |
| France | 100 | 100 | 100 |
| Greece | 23 | 14 | 20 |
| Hungary | 86 | 0 | - |
| Ireland | 0 | 0 | 0 |
| Italy | 88 | 78 | 100 |
| Lithuania | 0 | 0 | - |
| Latvia | 0 | 0 | 0 |
| Malta | 100 | 100 | 100 |
| Netherlands | 100 | 67 | 100 |
| Poland | 0 | 0 | 0 |
| Portugal | 100 | 67 | 100 |
| Sweden | 100 | - | - |
| Slovenia | 67 | 0 | 0 |
| Slovak Republic | 0 | - | - |
| United Kingdom | 13 | 0 | 0 |

*Notes*: The percentages in the table are based on the same estimates as Figure 6. ”-” indicates that a country does not have Objective 1 regions in the specified window.

Table 8: Local Average Treatment Effect (1-Way Threshold)

**Panel A: Bias of Average Treatment Effect**

| | Sharp RDD | | Fuzzy 1 RDD | | Fuzzy 2 RDD | |
|---|---|---|---|---|---|---|
| | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ |
| **Parametric** | | | | | | |
| $N = 60^2 \cdot 6$ | 0.012 | -0.061 | 0.013 | 0.015 | -0.068 | -0.076 |
| $N = 40^2 \cdot 6$ | 0.004 | -0.039 | 0.005 | 0.006 | -0.046 | -0.056 |
| $N = 20^2 \cdot 6$ | 0.017 | 0.116 | 0.022 | 0.031 | 0.147 | 0.203 |
| **Nonparametric** | | | | | | |
| Bandwidth 2/3 | -0.017 | -0.044 | -0.020 | -0.026 | -0.046 | -0.047 |
| Bandwidth 1/3 | -0.007 | -0.124 | -0.015 | -0.037 | -0.158 | -0.244 |
| Bandwidth 1/6 | 0.079 | -0.050 | 0.101 | 0.101 | -0.047 | -0.039 |

**Panel B: RMSE of Average Treatment Effect**

| | Sharp RDD | | Fuzzy 1 RDD | | Fuzzy 2 RDD | |
|---|---|---|---|---|---|---|
| | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ |
| **Parametric** | | | | | | |
| $N = 60^2 \cdot 6$ | 0.006 | 0.027 | 0.008 | 0.010 | 0.033 | 0.042 |
| $N = 40^2 \cdot 6$ | 0.014 | 0.062 | 0.019 | 0.027 | 0.082 | 0.116 |
| $N = 20^2 \cdot 6$ | 0.061 | 0.237 | 0.098 | 0.183 | 0.379 | 0.712 |
| **Nonparametric** | | | | | | |
| Bandwidth 2/3 | 0.010 | 0.040 | 0.013 | 0.019 | 0.054 | 0.079 |
| Bandwidth 1/3 | 0.027 | 0.109 | 0.043 | 0.089 | 0.176 | 0.368 |
| Bandwidth 1/6 | 0.126 | 0.488 | 0.193 | 0.472 | 0.741 | 1.788 |

*Notes*: All estimates result from Monte Carlo simulations with 2000 replications. The random error terms in the outcome equation as well as the random process underlying the fuzziness are drawn for each replication separately. The nonparametric estimates result from local linear regressions with uniform kernel. The variance of the error term in the outcome equation is denoted by $\sigma_\epsilon$. Fuzzy 1 (2) refers to a data generating process with a misassignment probability of 1/12 (1/6) within 5 bins at both sides of the threshold. The largest sample refers to a grid range $[-2.95, 2.95]$ with 0.1 intervals. Accordingly, $x$ and $z$ feature 60 different values each. We observe each $x - z$ combination 6 times. The bias as well as the RMSE of the average treatment effect are measured in percent.

## Table 9: Local Average Treatment Effects (2-Way Threshold)

**Panel A: Bias of Average Treatment Effect**

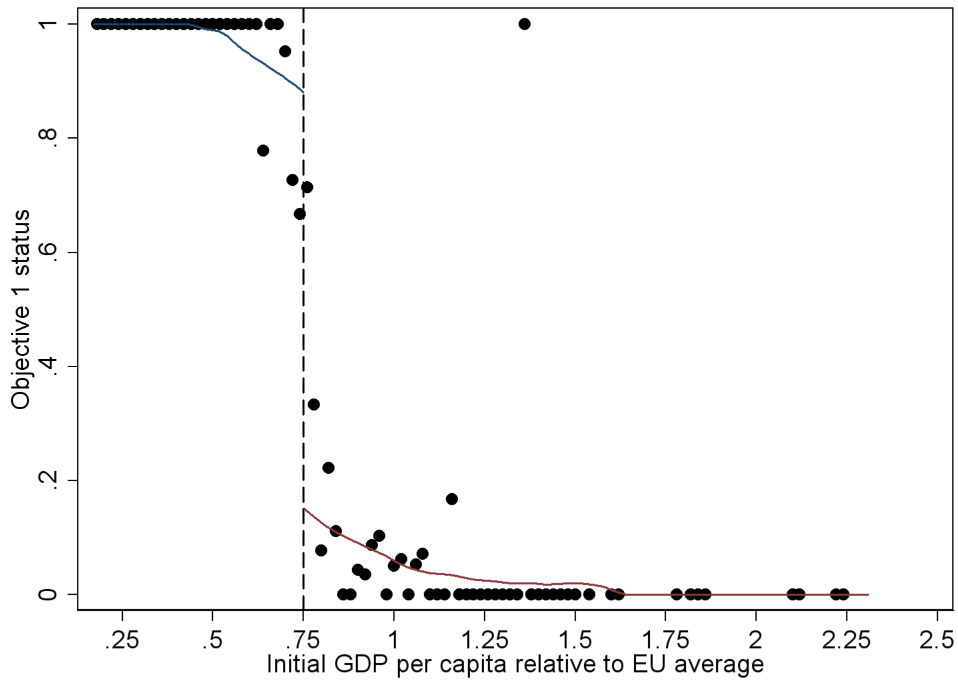
| | Sharp RDD | | Fuzzy 1 RDD | | Fuzzy 2 RDD | |
|---|---|---|---|---|---|---|
| | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ |
| **Parametric** | | | | | | |
| $N = 60^2 \cdot 6$ | 0.012 | -0.097 | 0.012 | 0.013 | -0.098 | -0.101 |
| $N = 40^2 \cdot 6$ | 0.047 | 0.051 | 0.049 | 0.051 | 0.053 | 0.056 |
| $N = 20^2 \cdot 6$ | -0.001 | 0.175 | -0.003 | -0.005 | 0.181 | 0.188 |
| **Nonparametric** | | | | | | |
| Bandwidth 2/3 | -0.004 | -0.079 | -0.002 | 0.005 | -0.088 | -0.099 |
| Bandwidth 1/3 | 0.026 | -0.088 | 0.032 | 0.041 | -0.087 | -0.091 |
| Bandwidth 1/6 | 0.077 | -0.035 | 0.072 | 0.053 | -0.019 | 0.049 |

**Panel B: RMSE of Average Treatment Effect**

| | Sharp RDD | | Fuzzy 1 RDD | | Fuzzy 2 RDD | |
|---|---|---|---|---|---|---|
| | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ | $\sigma_\epsilon = 0.3$ | $\sigma_\epsilon = 0.6$ |
| **Parametric** | | | | | | |
| $N = 60^2 \cdot 6$ | 0.007 | 0.027 | 0.007 | 0.008 | 0.028 | 0.029 |
| $N = 40^2 \cdot 6$ | 0.014 | 0.058 | 0.015 | 0.016 | 0.062 | 0.066 |
| $N = 20^2 \cdot 6$ | 0.054 | 0.197 | 0.059 | 0.067 | 0.218 | 0.247 |
| **Nonparametric** | | | | | | |
| Bandwidth 2/3 | 0.016 | 0.066 | 0.017 | 0.018 | 0.069 | 0.075 |
| Bandwidth 1/3 | 0.042 | 0.165 | 0.047 | 0.061 | 0.185 | 0.243 |
| Bandwidth 1/6 | 0.159 | 0.599 | 0.185 | 0.290 | 0.691 | 1.081 |

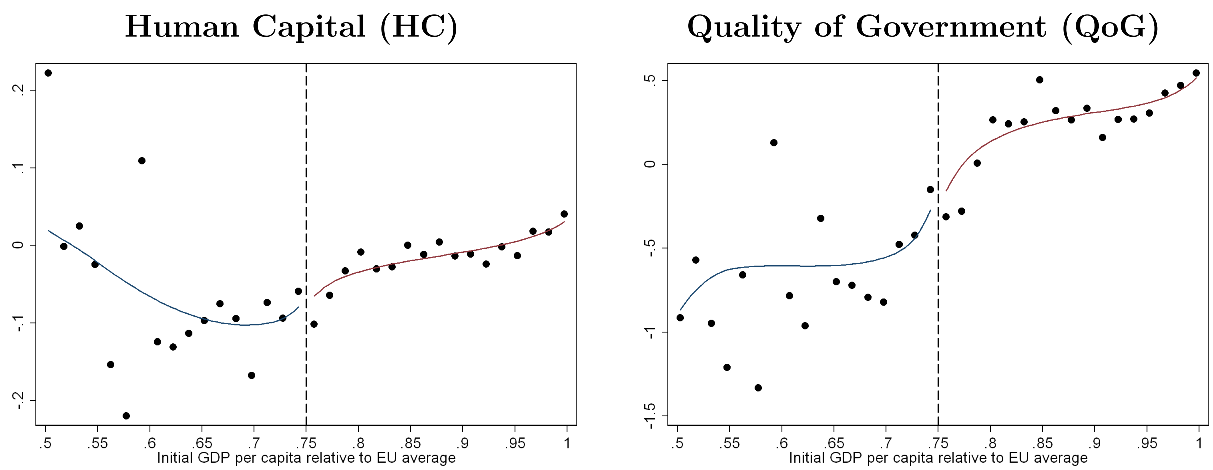
*Notes*: All estimates result from Monte Carlo simulations with 2000 replications. The random error terms in the outcome equation as well as the random process underlying the fuzziness are drawn for each replication separately. The nonparametric estimates result from local linear regressions with uniform kernel. The variance of the error term in the outcome equation is denoted by $\sigma_\epsilon$. Fuzzy 1 (2) refers to a data generating process with a misassignment probability of 1/12 (1/6) within 5 bins at both sides of the two dimensional threshold. The largest sample refers to a grid range $[-2.95, 2.95]$ with 0.1 intervals. Accordingly, $x$ and $z$ feature 60 different values each. We observe each $x - z$ combination 6 times. The bias as well as the RMSE of the average treatment effect are measured in percent.

Figure 1: Objective 1 status and the 75% GDP threshold



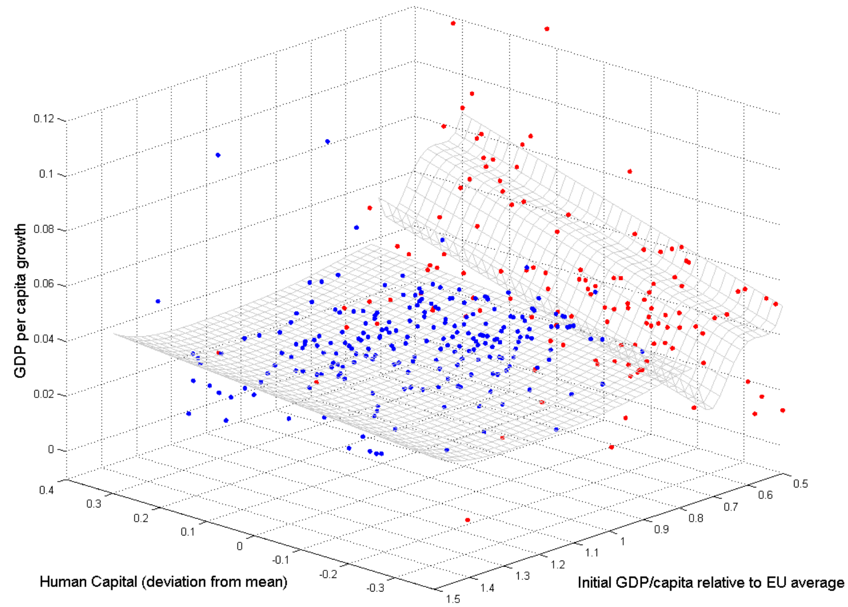

*Note*: The figure shows average treatment rates in equally-sized bins of 1.5 percentage points which are plotted against the per-capita GDP level that applied in the years relevant for the decision about Objective 1 status. The graph represents a local polynomial smooth based on an Epanechnikov kernel with a rule-of-thumb bandwidth. Note that the outlier at about 1.3 times the EU average which received treatment represents only one observation, namely Berlin in the 1989-1993 programming period. All results are robust to the exclusion of Berlin.

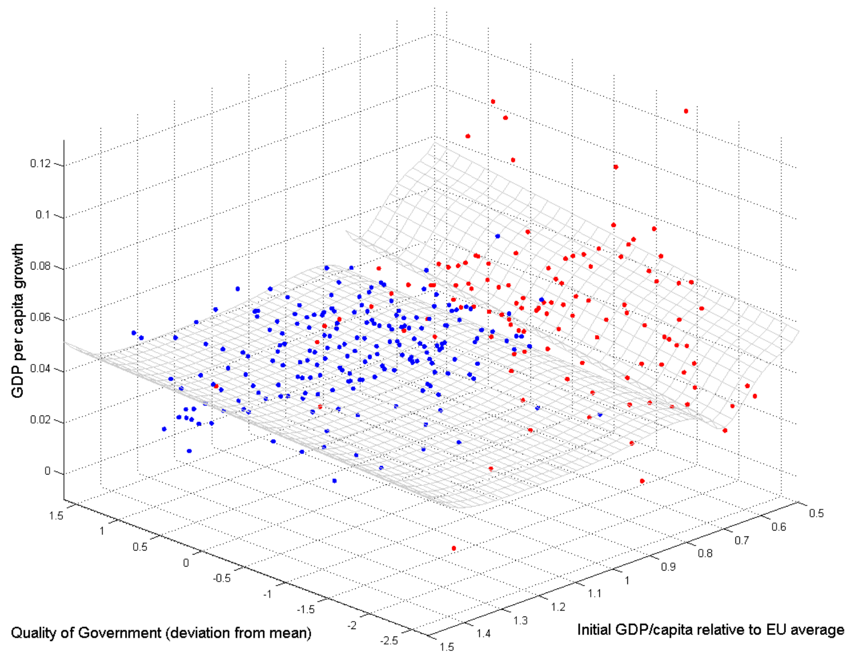
Figure 2: Human Capital, Quality of Government and the 75% GDP threshold




*Note*: The figures show averages of HC and QoG in equally-sized bins of 1.5% which are plotted against the per-capita GDP level that applied in the years relevant for the decision about Objective 1 status. The graphs represent a 2nd-order local polynomial function.

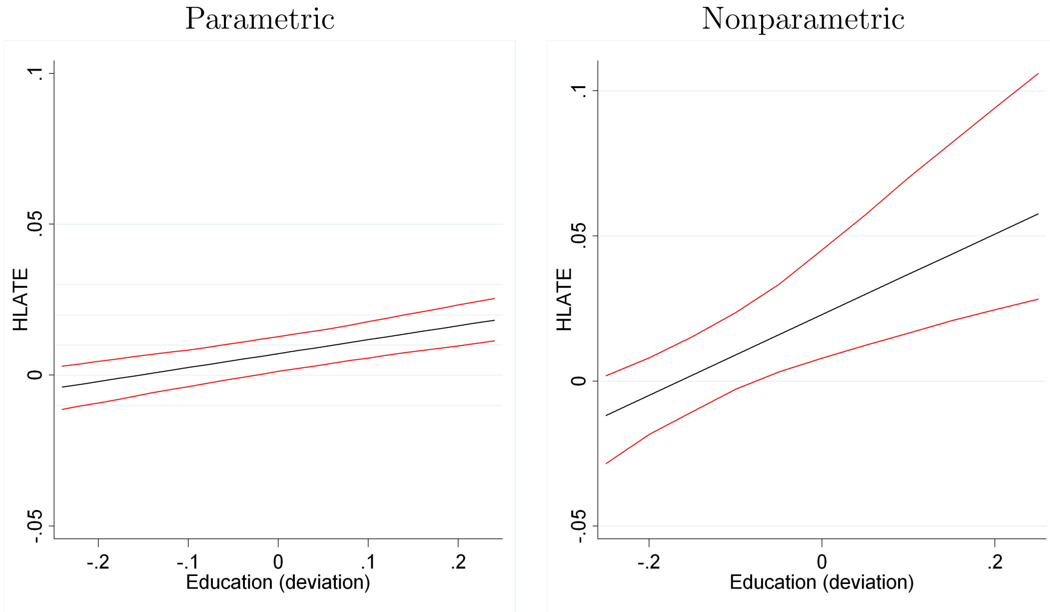
Figure 3: Objective 1 Treatment, Human Capital, and Quality of Government



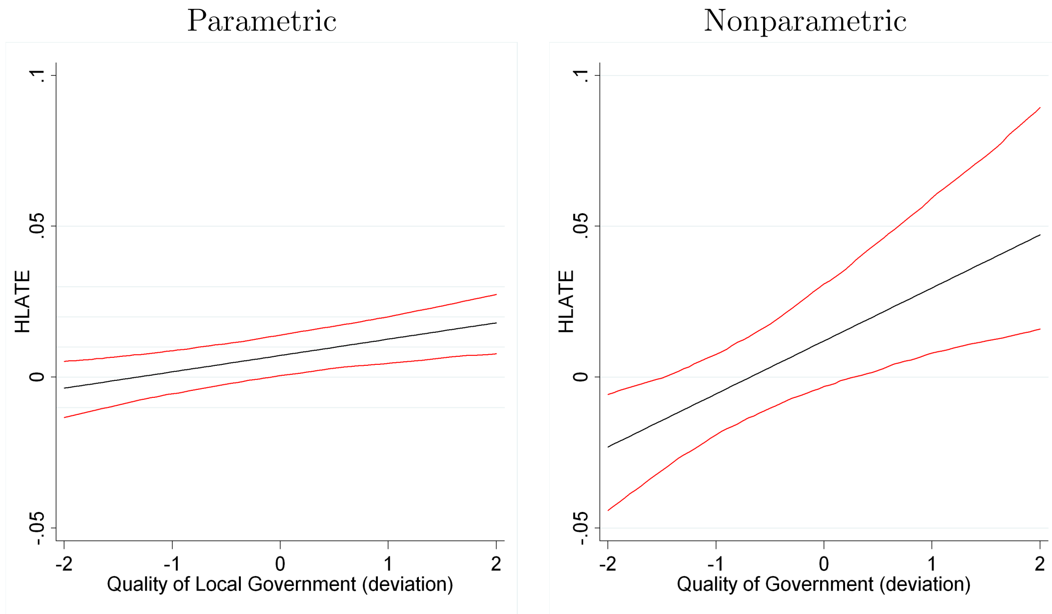

*Note*: The upper and lower figures illustrate the relationship between the outcome, forcing variable, human capital, and quality of government, respectively. The red (blue) dots indicate observations which received (did not receive) Objective 1 treatment. The surfaces represent 5th-order polynomial functions of per-capita GDP and linear functions of human capital and quality of government, respectively. These functions are estimated on both sides of the 75% threshold separately.

Figure 4: HLATE for different levels of Human Capital



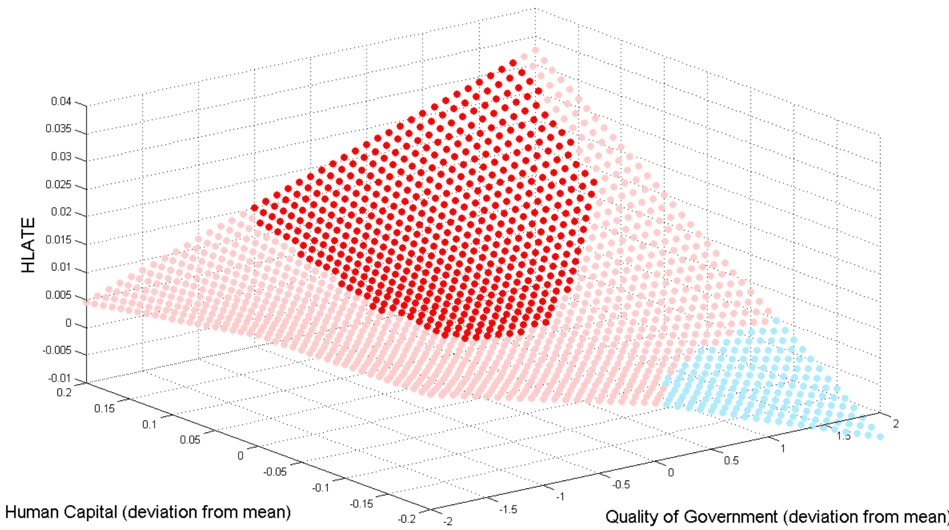

*Note*: The black line illustrates the point estimates, the red lines represent the 90% confidence intervals. The parametric estimates are derived from a specification with 3rd-order polynomials of initial GDP per-capita and linear human capital. The nonparametric estimates are based on an optimal bandwidth selection procedure following Ludwig and Miller (2007). We choose the optimal bandwidth for the conditional expectations of treatment and outcome separately. The confidence intervals are derived from bootstrapped standard errors with 1000 replications.

Figure 5: HLATE for different levels of Quality of Government




*Note*: The black line illustrates the point estimates, the red lines represent the 90% confidence intervals. The parametric estimates are derived from a specification with 3rd-order polynomials of initial GDP per capita and linear quality of government. The nonparametric estimates are based on an optimal bandwidth selection procedure following Ludwig and Miller (2007). We choose the optimal bandwidth for the conditional expectations of treatment and outcome separately. The confidence intervals are derived from bootstrapped standard errors with 1000 replications.

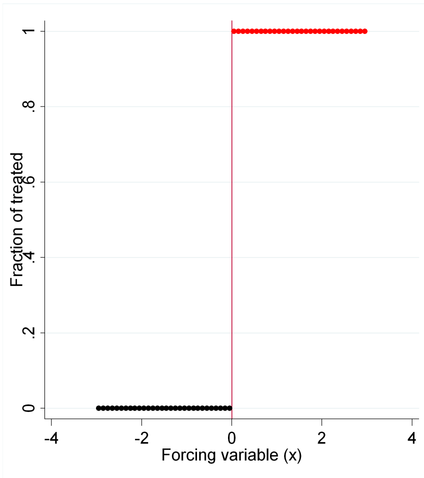
Figure 6: HLATE for different levels of Human Capital (HC) and Quality of Government (QoG): Parametric estimation



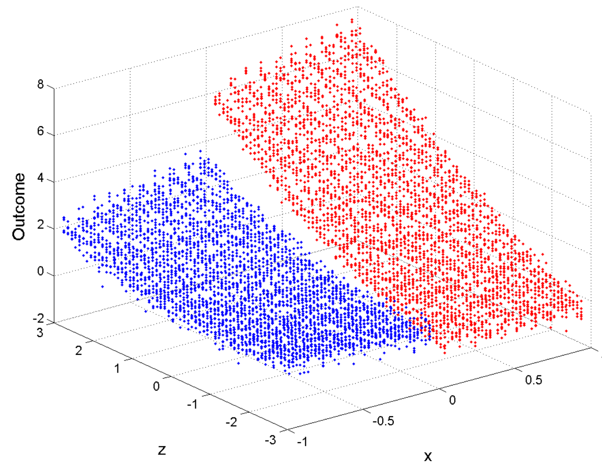

*Note*: The light red and light blue areas refer to insignificant positive and insignificant negative effects, respectively. The dark red area indicates significant positive effects. We choose the 90% confidence interval – calculated on the basis of bootstrapped standard errors – to determine significance of the HLATE. The predictions stem from parametric OLS regressions with a 3rd-order polynomial of per-capita GDP and linear HC and QoG.

Figure 7: Sharp RDD (1-Way Threshold)

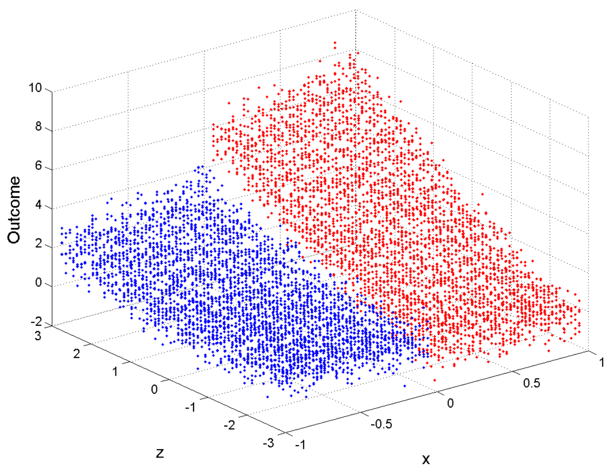
Treatment




Outcome ($\sigma_\epsilon = 0.3$)

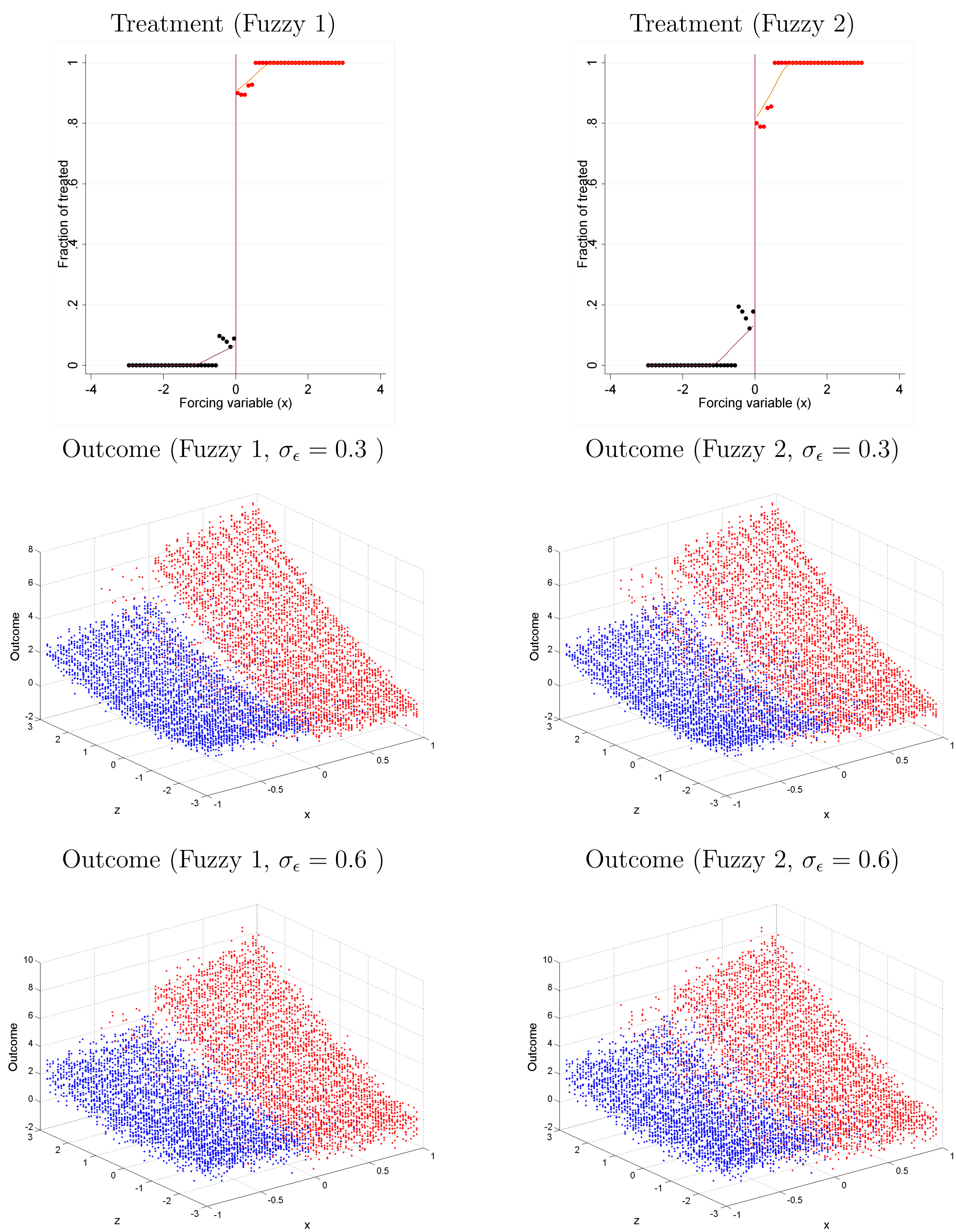



Outcome ($\sigma_\epsilon = 0.6$)



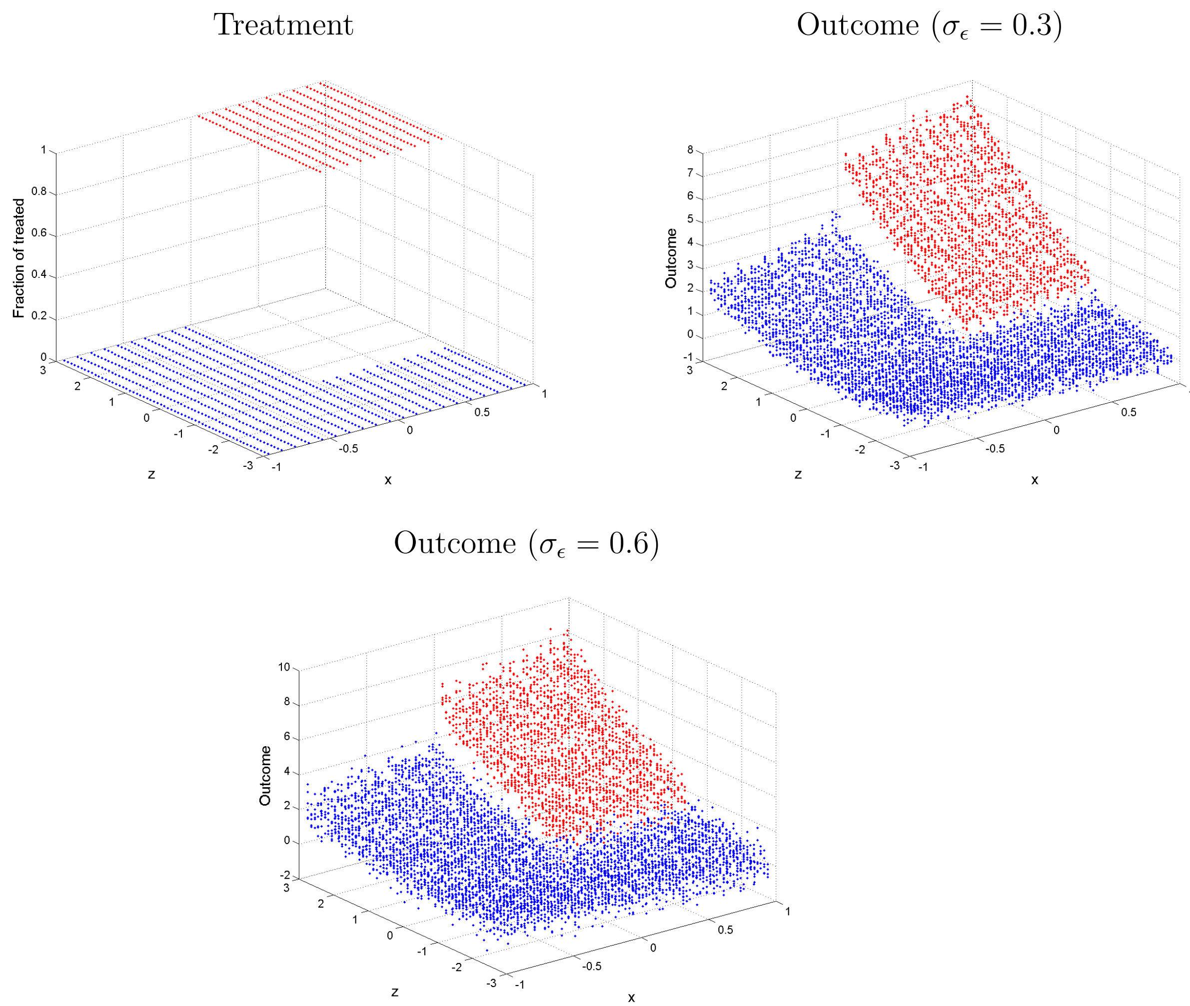

*Note*: The upper left figure shows average treatment rates in equally-sized bins of 0.1 which are plotted against the forcing variable $x$. The other two figures show average outcome rates plotted against the forcing variable $x$ and the interaction variable $z$. Blue (red) dots indicate untreated (treated) observations. For illustration purpose, we focus on the range $x = [-1, 1]$. $\sigma_\epsilon$ refers to the standard deviation of the error term in the outcome function. That is, the greater is $\sigma_\epsilon$ the less precise is the control function of $x$.

Figure 8: Fuzzy RDD (1-Way Threshold)



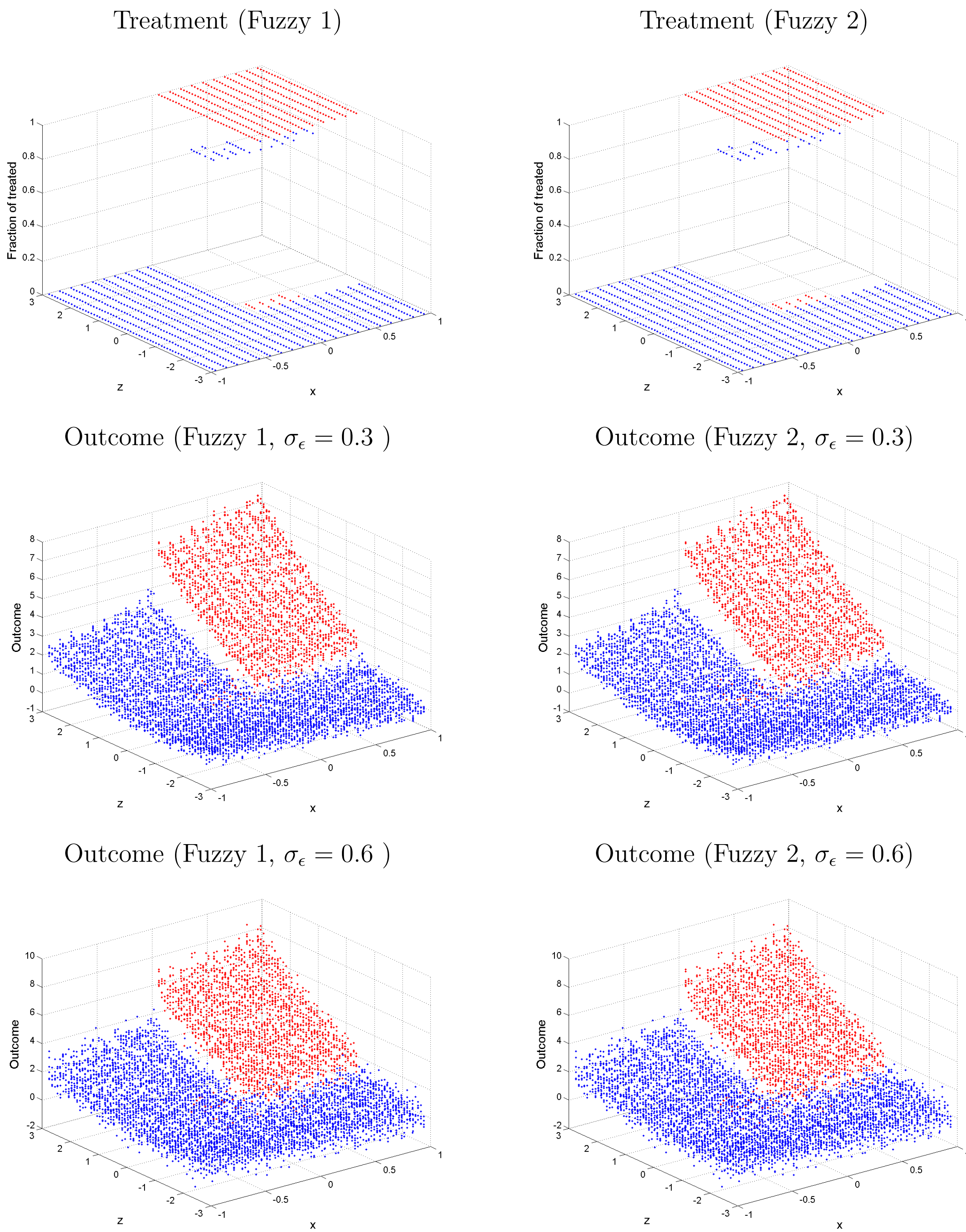

*Note*: The upper figures show average treatment rates in equally-sized bins of 0.1 which are plotted against the forcing variable $x$. The figures in the two lower panels show average outcome rates plotted against the forcing variable $x$ and the interaction variable $z$. Blue (red) dots indicate to untreated (treated) observations. For illustration purpose, we focus on the range $x = [-1, 1]$. $\sigma_\epsilon$ refers to the standard deviation of the error term in the outcome function while Fuzzy 1 (2) indicates a misassignment probability of 1/12 (1/6). Accordingly, the greater is $\sigma_\epsilon$ the less precise is the control function of $x$, and Fuzzy 2 represents a less precise relationship between the treatment the treatment rule than Fuzzy 1.

Figure 9: Sharp RDD (2-Way Threshold)



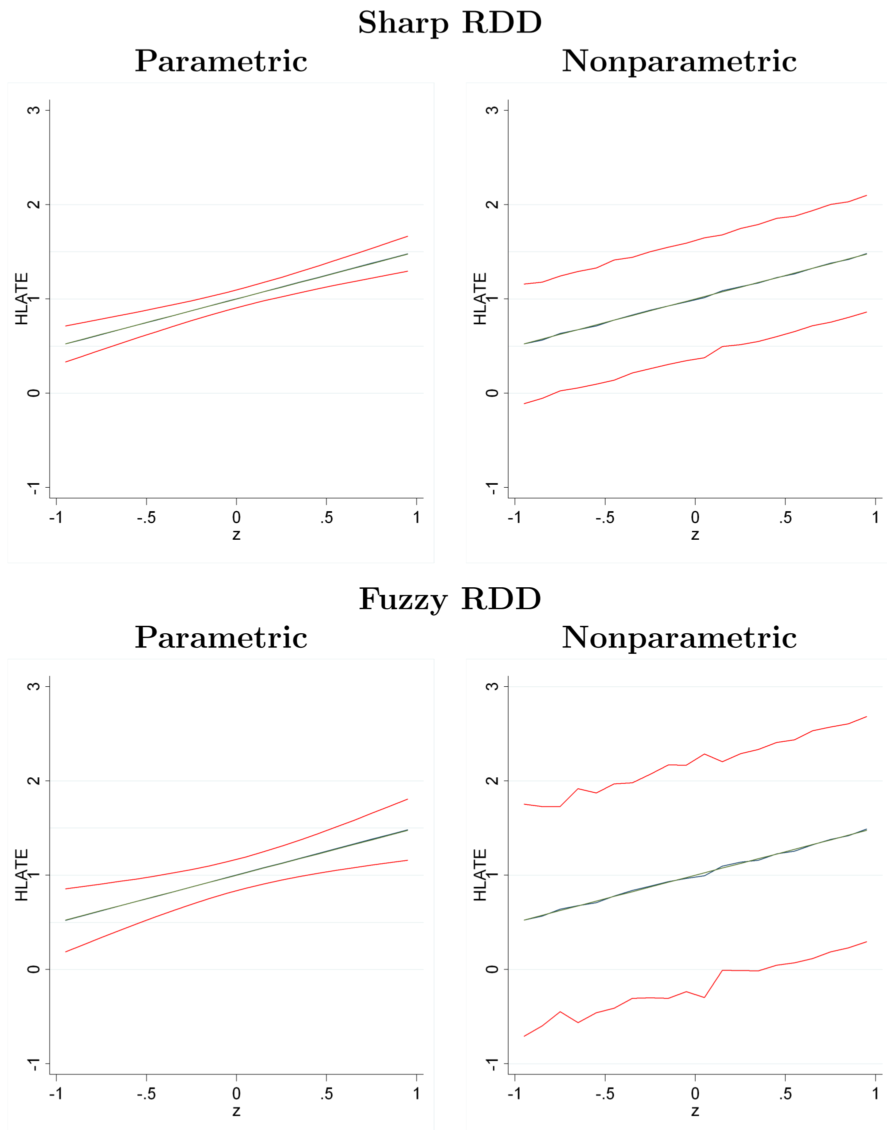

*Note*: The upper left figure shows average treatment rates in equally-sized bins of 0.1 which are plotted against the two forcing variables $x$ and $z$. The other two figures show average outcome rates plotted against the forcing variables $x$ and $z$. In addition to determining the treatment probability, $z$ affects the treatment effect via an interaction term in the outcome equation. $\sigma_\epsilon$ refers to the standard deviation of the error term in the outcome function. That is, the greater is $\sigma_\epsilon$ the less precise is the control function of $x$.

Figure 10: Fuzzy RDD (2-Way Threshold)



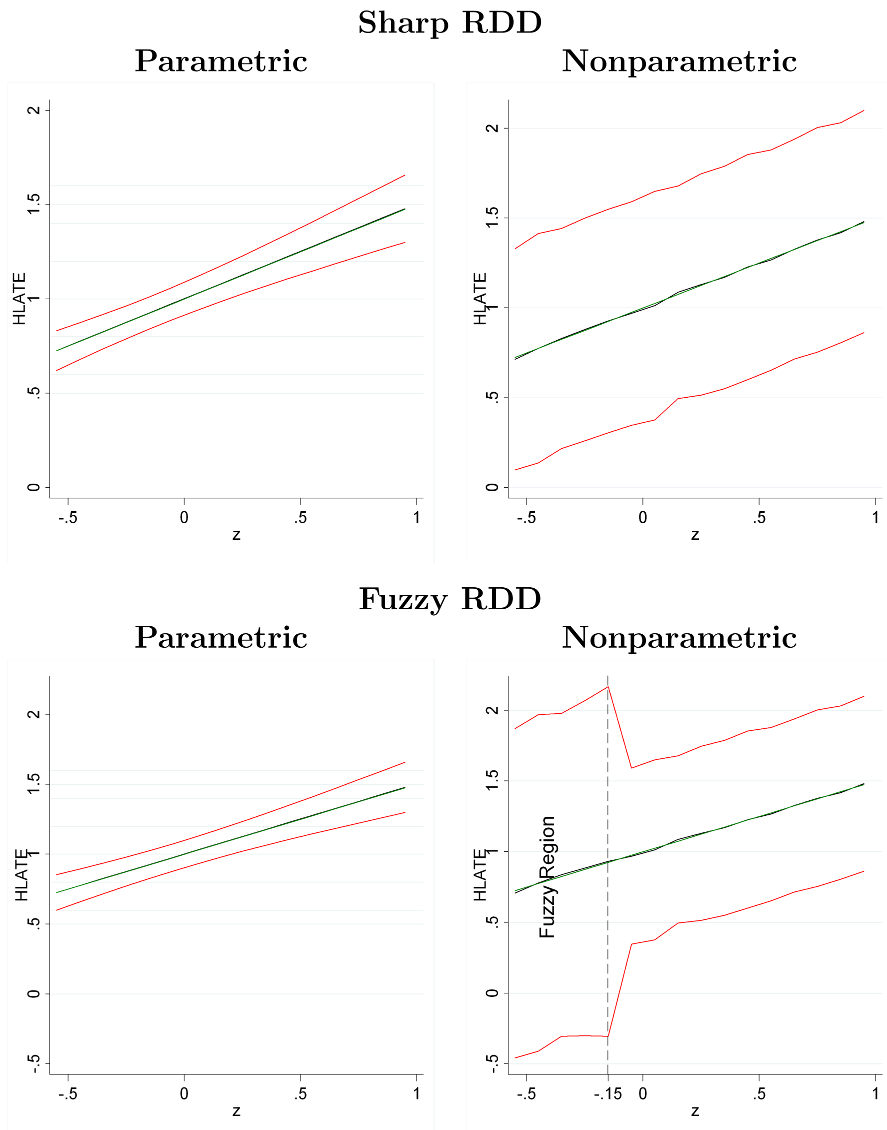

*Note*: The upper figures show average treatment rates in equally-sized bins of 0.1 which are plotted against the forcing variables $x$ and $z$ where red (blue) dots indicate observations that qualify (do not qualify) for treatment according to the treatment rule. The figures in the two lower panels show average outcome rates plotted against the forcing variables $x$ and $z$ where red (blue) dots indicate observations that did (did not) receive treatment. In addition to determining the treatment probability, $z$ affects the treatment effect via an interaction term in the outcome equation. $\sigma_\epsilon$ refers to the standard deviation of the error term in the outcome function, while Fuzzy 1 (2) indicates a misassignment probability of 1/8 (1/4). Accordingly, the greater is $\sigma_\epsilon$ the less precise is the control function of $x$, and $z$, and Fuzzy 2 represents a less precise relationship between the treatment the treatment rule than Fuzzy 1.

Figure 11: Heterogenous local average treatment effects (1-Way Threshold)



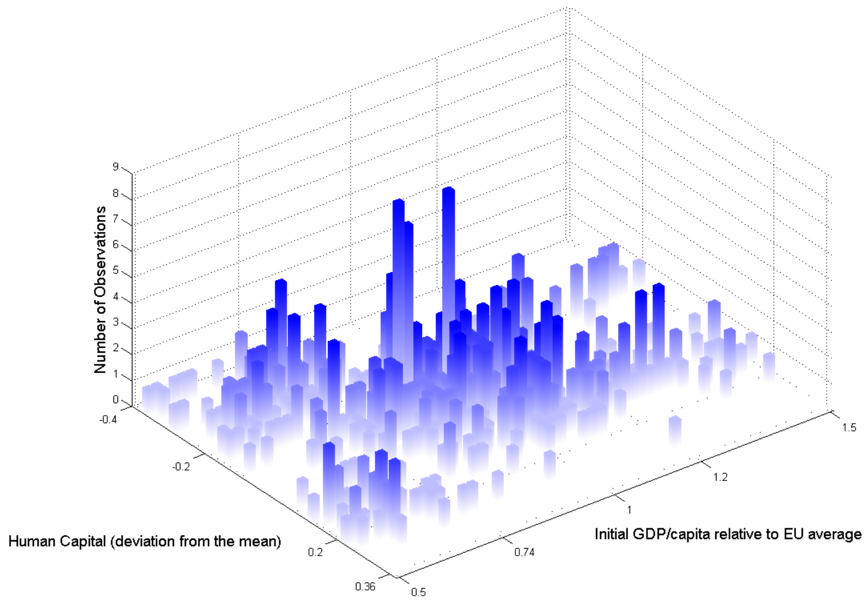

*Note*: The figures show treatment effects at the $x_0$ threshold (we restrict the sample to one bin on each side of $x_0$) plotted against the interaction variable $z$. All figures are based on experiments with $\sigma_\epsilon = 0.6$ where the fuzzy design refers to a data-generating process with a misassignment probability 1/6. The parametric figures are derived from an $N = 20^2 \cdot 6$ sample. For the nonparametric figures, we choose a bandwidth of 1/6. The green line illustrates the true effect, the black line illustrates the point estimates, and the red lines represent the 90% confidence intervals.

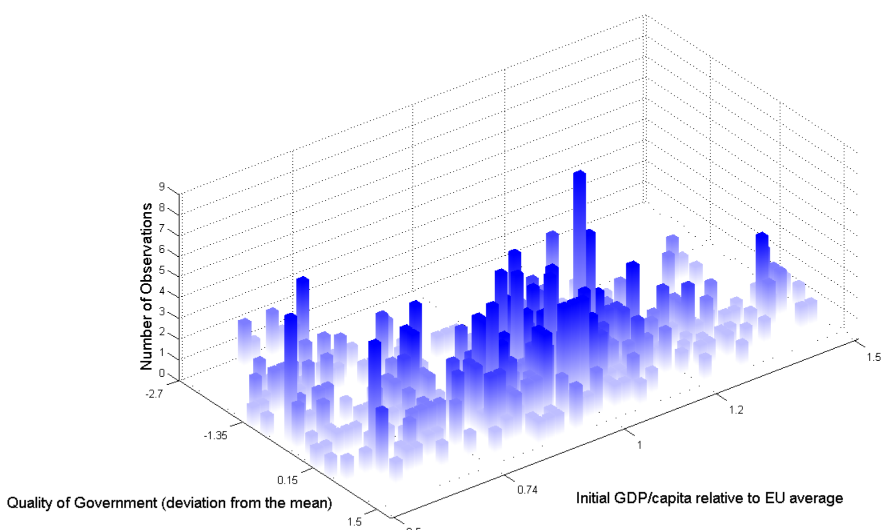
Figure 12: Heterogenous local average treatment effects (2-Way Threshold)




*Note*: The figures show treatment effects at the $x_0$ threshold (we restrict the sample to one bin on each side of $x_0$) plotted against the interaction variable $z$. All figures are based on experiments with $\sigma_\epsilon = 0.6$ where the fuzzy design refers to a data-generating process with a misassignment probability 1/6. Note that the fuzzyness is bounded in the $z$ dimension by [-1.05, -0.15] which results in a lower degree of precision of the HLATE in this interval. The parametric figures are derived from an $N = 20^2 \cdot 6$ sample. For the nonparametric figures, we choose a bandwidth of 1/6. The green line illustrates the true effect, the black line illustrates the point estimates, and the red lines represent the 90% confidence intervals.

Figure 13: Frequency plots




*Note*: The upper and lower figures illustrate the number of observations in the human capital/per-capita GDP bins and the quality of government/per-capita GDP bins, respectively. These bins correspond to the ones used in Figure 3.