Too much of a good thing?
On the growth effects of the EU's regional policy*

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Abstract

The European Union (EU) provides grants to disadvantaged regions of member states from two pools, the Structural Funds and the Cohesion Fund. The main goal of the associated transfers is to facilitate convergence of poor regions (in terms of per-capita income) to the EU average. We use data at the NUTS3 level from the last two EU budgetary periods (1994-99 and 2000-06). Using generalized propensity score estimation, we analyze to which extent the goal of fostering growth in the target regions was achieved with the funds provided and whether more transfers generated stronger growth effects or not. We find that, overall, EU transfers enable faster growth in the recipient regions as intended, but we estimate that in 36% of the recipient regions the transfer intensity exceeds the aggregate efficiency maximizing level and in 18% percent of the regions a reduction of transfers would not even reduce their growth. We conclude that some reallocation of the funds across target regions would lead to higher aggregate growth in the EU and could generate even faster convergence than the current scheme does.

Keywords: EU regional policy; Regional growth; Generalized propensity score estimation; Quasi-randomized experiment

JEL Classification: C21; O40; H50; R11

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1 Introduction

As the budget of the European Union (EU) becomes tighter and major recipients of European regional transfers struggle with debt crises, questions about the proper utilization and effectiveness of transfers from the central EU budget to Europe's poorest regions are hotly debated. Since 1975, when the European Regional Development Fund (ERDF) was founded, a significant budget has been devoted to the reduction of regional imbalances, especially, in terms of per-capita income.[1] The Treaty of Lisbon which entered into force in 2009 acknowledges *regional cohesion* as one of the key goals of the European Union.[2]

The Union's regional policy goals are rooted in the perception that a common market requires a certain degree of homogeneity in economic development which is not necessarily an automatic outcome of the integration process but, eventually, has to be assisted by active policy interventions. Accordingly, with the EU enlargements to the south[3] and, more recently, to the east,[4] the disparities among the member countries of the Union increased sharply, and so did the scope of regional transfers. During the 1975-88 programming period, the ERDF budget represented on average 6.8 percent of the total Community budget, while during the current 2007-13 programming period the cohesion policy's expenses make up 35.7 percent of the total Community budget, or 347.41 billion Euros at current prices (see European Commission, 1989, 2008). These expenses stem from different funds: the ERDF contributes about 58 percent, the European Social Fund (ESF) about 22 percent, and the Cohesion Fund about 20 percent. The ERDF and the ESF are commonly referred to as the Structural Funds where the former focuses on infrastructure investments and the latter on employment measures.[5] The Cohesion Fund was established in the treaty of Maastricht and is intended to support the Structural Funds in strengthening the economic and social cohesion in the Union. The Cohesion Fund mainly finances environmental projects and trans-European transport infrastructure networks. In

[1]The European Social Fund (ESF) and the European Agricultural Guidance and Guarantee Fund (EAGGF) were already founded in 1958 and 1962, respectively, but were focused on specific duties and were limited in scope. The Cohesion Fund was founded as late as 1992.

[2]Article 174 of the Treaty on the Functioning of the European Union states: "[...] the Union shall aim at reducing disparities between the levels of development of the various regions and the backwardness of the least favored regions" (see Official Journal C 115/127 09/05/2008).

[3]Greece joined the EU in 1981, and Spain and Portugal in 1986.

[4]Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, the Slovak Republic, and Slovenia joined in 2004, and Bulgaria and Romania in 2007.

[5]Until 2006, the Structural Funds included the European Agricultural Guidance and Guarantee Fund (EAGGF) and the Financial Instrument for Fisheries Guidance (FIFG) which have been replaced by the European Agricultural Fund for Rural Development (EAFRD) and the European Fisheries Fund (EFF), respectively. Both funds are no longer directly involved in cohesion policy.

contrast to the Structural Funds, the Cohesion Fund operates on the national rather than the regional level.[6]

The heterogeneity of regional transfer intensity – defined as the amount of EU transfers, in percent of a target region's beginning-of-period GDP – across recipient regions and programming periods is remarkable. To see this, let us focus on the level of so-called NUTS3 regions, which are regional entities of between 150-800 thousand inhabitants. [7] Table 1 shows that the poorest NUTS3 region – in terms of GDP per capita at Purchasing Power Parity prior to the beginning of the respective programming period –, in Greece, received annual transfers from the EU's Structural and Cohesion Funds of about 29 percent of its year 1993 GDP level in the 1994-99 programming period. Among the recipients of such transfers in that period, Coburg in Germany received only about 0.002 percent of its year 1993 GDP level. Notice that the variation in regional transfer intensity at the NUTS3 regional level has three roots: first, the variation in GDP (and per-capita GDP) across NUTS3 regions; second, the variation in transfers to countries, NUTS2 regions[8] and NUTS3 regions as provided by the European Commission;[9] third, the discretion at the national level or the level of NUTS2 regions about the allocation of funds to NUTS3 entities which fall into their jurisdiction.

It is sometimes argued that some regions use EU transfers increasingly inefficiently, the higher the transfers they receive. Due to a lack of administrative capacity, the funds are not spent as intended but are used for consumption purposes or are subject to corruption.[10] If there are diminishing returns to EU regional transfers, knowing that they foster growth *on average*, as in Becker, Egger, and von Ehrlich

[6]Member states qualify for transfers from the Cohesion Fund if their GDP per capita falls below 90% of the community average. The most significant amount of Structural Funds is transferred to NUTS2 regions with a per-capita GDP below 75% of the community average (so-called Objective 1 regions).

[7]The counterpart to a NUTS3 region in the United States would be a county. In France, they represent *Départements*, in Germany, they are equivalent to *Landkreise*, in Spain, they correspond to *Comunidades Autónomas*, and in the United Kingdom, they are associated with the *Unitary Authorities*.

[8]NUTS2 regions are somewhat larger clusters of NUTS3 regions measuring between 0.8 and 3 million inhabitants.

[9]For some types of transfers, such as those falling under the auspices of Objective 1 in the Structural Funds Programme, eligibility for transfers is determined at the level of NUTS2 regions (with a few exceptions which determine transfers to NUTS3 regions; see Becker, Egger, and von Ehrlich, 2010, for a detailed description of the rules for Objective 1 treatment). Other types of transfers are determined at the NUTS3 level or the national level.

[10]See euobserver.com from October 20, 2009, "EU funds still vulnerable to fraud in Bulgaria", Handelsblatt from March 2, 2010 "Korrumpierter Staatsapparat: EU duldet Griechenlands Betrug seit Jahren", the New York Times from August 23, 2008, "EU cuts back funding to Bulgaria", or euractive.com from December 8, 2008, "Time to redesign the Structural Funds system".

(2010), is not enough. [11] In fact, it is important to understand how a varying treatment *intensity* (different amounts of EU transfers relative to GDP) affects regional growth. This will allow us to see up to which level transfers serve the intended goal of fostering regional growth and beyond which a further allocation of funds becomes inefficient. Estimation of that threshold for the EU's regional policy programmes calls for an identification strategy that goes beyond a binary transfer indicator and exploits variation in transfer intensity.

An argument for a declining treatment effect – and, eventually, existence of a *maximum desirable level of regional transfers* – arises naturally from neoclassical production theory and the assumption of diminishing returns to investment (and investment-stimulating transfers); see Hirshleifer (1958). Suppose that investment projects are financed and undertaken in the order of expected returns on investment. Then, a bigger number of investment projects carried out would be associated with a lower return to investments (or transfers). If diminishing returns to transfers were relevant, we could identify a maximum desirable level of the treatment intensity above which no additional (or even lower) per-capita income growth effects were generated than at or below the threshold.

There is a similar argument for a *minimum necessary level of regional transfers* which is based on the big-push or poverty-trap theory of development, which states that transfers (or aid) have to exceed a certain threshold in order to become effective. For instance, this would be the case if the marginal product of capital were extremely low at too small levels of infrastructure or human capital (see Sachs, McArthur, Schmidt-Traub, Kruk, Bahadur, Faye, and McCord 2004). Alternatively, this could be the case if regions lagging behind were isolated from other developed regions (see Murphy, Shleifer, and Vishny 1989, for arguments along those lines). If the big-push or poverty-trap theory applied to the least-developed NUTS3 regions in the EU, one would expect to find a minimum desirable level of regional transfer intensity below which transfers would not generate positive growth effects but above which

[11] Becker, Egger, and von Ehrlich (2010) provide an overview of the literature on the effects of the EU's regional transfers and conduct an evaluation of Objective 1 transfers, which make up two thirds of the EU's Structural Funds Programme. More specifically, Becker, Egger, and von Ehrlich (2010) use a binary treatment indicator in a regression discontinuity design to study the causal effects of Objective 1 funds on GDP per capita growth in recipient versus non-recipient regions. The discontinuity arises from the rule that EU regions whose GDP per capita falls below 75% of the EU average are eligible for Objective 1 funds whereas regions above the 75% threshold are ineligible. Their results suggest that, in a best-case scenario, Objective 1 transfers generate a multiplier of approximately 1.2 so that every Euro of transfers generates 20 extra cents of GDP. However, that multiplier effect relates to Objective 1 treatment only, since other parts of the Structural and Cohesion Funds do not follow a clearly defined rule (75% threshold) and do not lend themselves to a regression discontinuity design for identification.

they would. Then, it would be reasonable to focus the limited transfer budget on a few very poor regions in order to ensure that the transfers are sufficient to have a noticeable effect.

With regions above a maximum desirable treatment intensity or below a minimum necessary treatment intensity, the overall EU budget could be reduced without any negative growth effects and, hence, there would be scope for unambiguous efficiency gains. In this analysis we also ask what the empirically *optimal transfer intensity* is. This will be the transfer level above which an additional Euro transferred yields less than additional Euro of additional GDP and below which it yields more than a Euro of additional GDP in the targeted region, i.e. the transfer intensity where the transfer multiplier is identical to one. Accordingly, if the transfer intensity exceeded the optimal one, a reallocation might hurt the concerned region but would enhance aggregate growth.

In this paper, we aim at identifying the functional form of the relationship between EU regional transfer intensity and per-capita income growth. It is empirically represented by the so-called dose-response function and shows how GDP per-capita growth responds to changes in EU transfer *intensity* at the regional NUTS3 level.[12] Unlike the study of Becker, Egger, and von Ehrlich (2010) and other studies using a binary indicator for EU regional transfer treatment, the dose-response function allows us to ask to which extent the European Commission in conjunction with regional authorities at the national or subnational levels provide and use transfers in an efficient – here to be interpreted as *per-capita-income growth maximizing* – way.[13] We identify the GDP per-capita growth-maximizing transfer intensity, which allows us to determine how many and which regions receive too much funding and how many and which regions receive too little funding out of the Structural and Cohesion Funds Programme.

Our results for the two programming periods 1994-99 and 2000-06 point to a non-linear relationship between the treatment intensity of EU regional transfers and per-capita growth. More specifically, we find evidence of a *maximum desirable treatment intensity*. At a transfer intensity beyond this level, the Null hypothesis of zero (or even negative) growth effects induced by additional transfers can no longer be rejected. At treatment intensities below this maximum desirable treatment intensity, per-capita income growth in the recipient regions could be raised significantly by

[12]Earlier studies by Becker, Egger, von Ehrlich, and Fenge (2008) and Hagen and Mohl (2008) used variation in the extent of transfers but did not have access to data at the disaggregated NUTS3 level as we do now, so that robust identification of the functional relationship between EU regional transfer intensity and per-capita income growth effects was not possible there.

[13]Note that we take the revenue side of the EU budget as given, i.e. we disregard the (hardly quantifiable) efficiency costs of raising the necessary tax revenue for transfers and the costs associated with the potential distortion of the regional allocation of economic activity.

providing higher transfers (at given GDP) up to the *maximum desirable treatment intensity*. Contrary to the big push hypothesis, within the EU there is no evidence for the existence of a minimum necessary level of regional transfers to induce positive per-capita income growth effects.
Our estimates suggest that, up to a *maximum desirable treatment intensity* of about 1.3 percent of a region's GDP, EU transfer receipts from Structural Funds or the Cohesion Fund lead to positive marginal income growth effects. However, beyond a treatment intensity of 1.3 percent, per-capita income growth can on average not be increased any further through *additional* EU transfers. About 18 percent of NUTS3 recipient regions receive transfers above that threshold. According to our results, a reallocation of the transfers that are above the *maximum desirable treatment intensity* – would not harm the regions concerned, but might benefit other regions. When applying the stricter criterion of *optimal treatment intensity*, we find that transfers should not exceed a treatment intensity of about 0.4 percent. According to our estimates the transfer-multiplier fell short of unity for about 36 percent of NUTS3 recipient regions across the two periods under consideration. This leads to the conclusion that there is some scope for greater efficiency at the level of Structural and Cohesion Funds transfers regarding their growth-maximizing allocation.

The remainder of the paper is structured as follows. The next section presents details on the sources and the construction of data at the level of NUTS3 regions for the two programming periods 1994-99 and 2000-06. Also, that section summarizes descriptive statistics. Section 3 discusses the econometric methodology applied for the identification of causal effects of the EU's regional transfers on growth. Section 4 presents the results and interprets the findings against the background of efficiency. The last section concludes with a summary of the most important findings.

2 Data and descriptive statistics

Our data stems from several sources. Information on EU transfers to NUTS3 regions has been kindly provided by ESPON (European Spatial Planning Observation Network) and the European Commission. We link this data with information on various regional characteristics from Cambridge Econometrics' Regional Database and with a measure of countries' voting power in the EU Council (measured by the Shapley-Shubik, 1954, index) which is taken from Felsenthal and Machover (1998) for the first programming period and and from Widgren (2009) for the second programming period.

In total, our data-set consists of 2,280 observations out of which 2,078 received transfers through one of the two programmes considered here (Structural Funds or

Cohesion Fund). Of the 2,078 treated units, 702 classify as Objective 1 regions which received the lion's share (74 percent on average across the two programming periods) of the total EU transfers. 363 of the 2,078 treated units received transfers from the Cohesion Fund. Table 1 provides details on the number and characteristics of NUTS3 regions during the two programming periods 1994-99 and 2000-06. We combine two programming periods to get more precise estimates of the relationship between treatment intensity and per-capita income growth. Yet, NUTS3 regions of EU member countries as of 1999 are observed twice in the data while EU entrants during 2000-06 are observed only once. In our estimations, we adjust standard errors of parameters and confidence bounds of treatment effects to account for such repeated observations. Pooling more than two budgetary periods for NUTS3 regions is impossible since detailed information on treatment intensity for programming periods prior to 1994-99 is not available at this disaggregated level.

TABLE 1 ABOUT HERE

The EU spent about 21,934 mn. Euros on regional transfers per annum (out of the Structural Funds and the Cohesion Fund programmes) across the two periods under consideration, of which 2,952 mn. Euros were spent through the Cohesion Fund and 18,982 mn. Euros were transferred through the Structural Funds programmes. Objective 1 regions received per annum about 16,301 mn. Euros from the central EU budget across the two periods. Since Austria, Finland, and Sweden joined the EU only in 1995 they did not receive transfers for the whole programming period 1994-99, just as the accession countries in 2004 did not receive transfers for the whole 2000-06 programming period. Table 1 displays the average annual transfers per treated region adjusting for the number of years the respective regions actually received transfers. When using the respective relevant GDP of the year prior to the start of the programming period in the denominator, the average annual regional transfer intensity amounted to 0.759 percent for all regional transfers, to 1.991 percent for Objective 1 transfers only, and to 0.659 percent for Cohesion Fund transfers. While most of the NUTS3 regions receive some transfers from the central budget, there is considerable variation in the transfer intensity. Figure 1 displays the geographic distribution of total EU transfer per GDP for both programming periods under consideration.

In the subsequent analysis, we focus on those 2,078 observations which received regional transfers through either the Structural Funds or the Cohesion Fund programmes. As can be seen from the lower panel of Table 1, those regions' per-capita income measured at Purchasing Power Parity grew by about 4.2 percent per annum during the two considered programming periods.[14] However, there is a fair amount of variation in the data. Table 1 suggests that the minimum growth rate across NUTS3 regions was a decline by almost four percent per annum while the maximum growth rate was almost 14 percent per annum within the sample period.

FIGURE 1 AND TABLE 2 ABOUT HERE

In our empirical analysis we employ various covariates: the GDP per-capita (PPP) prior to the respective programming period, total regional employment, sectoral shares, population density, a measure of countries' voting power in the EU, a period dummy and a variable that indicates whether a region is located at the EU border. Table 2 provides descriptive statistics for the data used in our analysis where per-capita GDP, and the employment information are measured in logarithmic terms.

3 Generalized propensity scores

3.1 Methodology

To estimate the causal effect of transfer intensity on per-capita income growth, we resort to generalized propensity score estimation, a non-parametric method to estimate treatment effects conditional on observable determinants of treatment intensity. Propensity score matching represents a well-suited econometric technique for program evaluation as it is able to correct for selection bias by comparing units that are similar in terms of their observable characteristics. Following the seminal paper by Rosenbaum and Rubin (1983) propensity score matching became very popular in the case of binary treatment (see, e.g., Heckman, Ichimura, and Todd, 1997, Dehejia and Wahba, 1999). The binary case was extended to categorial multivalued treatment by Imbens (2000) and, more recently, to continuous treatments (see Hirano and Imbens 2004, Imai and van Dyk, 2004). In the following we outline the method developed by Hirano and Imbens (2004) and apply it to our research question.

Index a sample of observations by $i = 1, \ldots, N$ and consider the *unit-level dose-response function* of outcomes $Y_i(\tau)$ as a function of treatments $\tau \in \mathscr{T}$. We allow $\mathscr{T}$ to be an interval $[\tau_0, \tau_1]$ but restrict $\tau_0 > 0$ in order to focus on regions with positive transfers. In the binary case, the treatment would be restricted to $\mathscr{T} = \{0, 1\}$. However, our objective is not to analyze whether any treatment boosts growth or

[14]Per-capita income growth is expressed as an average change in log-transformed per-capita income.

not but to what extent a higher treatment intensity yields stronger effects than a lower treatment intensity and to derive the optimal treatment intensity. Employing the generalized propensity score methodology, we aim at estimating the average dose-response function across all regions i, $\mu(\tau) = E[Y_i(\tau)]$.
The key challenge is to compare regions with sufficiently similar characteristics but different treatment intensity in order to construct a quasi-experimental setting. For each observation i we observe the vector of covariates X_i, the treatment intensity T_i, and the outcome corresponding to the level of treatment received, $Y_i = Y_i(T_i)$. We drop the index i for simplicity and assume that $Y(\tau)_{\tau \in \mathscr{T}}, T, X$ are defined on a common probability space, that τ is continuously distributed with respect to a Lebesgue measure on $\mathscr{T}$, and that $Y = Y(T)$ is a well defined random variable.

In this setting, the definition of unconfoundedness for binary treatments was generalized by Hirano and Imbens (2004) to a definition of *weak unconfoundedness* for continuous treatments

$$Y(\tau) \quad \perp \quad T|X \quad \text{for all} \quad \tau \in \mathscr{T}. \tag{1}$$

Regions differ in their characteristics X such that some are more or less likely to receive a high treatment intensity than others. The weak unconfoundedness assumption says that, after controlling for observable characteristics X, any remaining difference in treatment intensity T across regions is independent of the potential outcomes $Y(\tau)$. Assumption (1) is called weak unconfoundedness because it does not require joint independence of all potential outcomes, $Y(\tau)_{\tau \in [\tau_0, \tau_1]}, T, X$. Instead, it requires conditional independence to hold at every treatment level.

The generalized propensity score is defined as

$$R = r(T, X), \tag{2}$$

where $r(\tau, x) = f_{T|X}(\tau|x)$ is the conditional density of the treatment given the covariates. Similar to the conventional propensity score under binary treatment, the generalized propensity score is assumed to have a *balancing property* which requires that, within strata of $r(\tau, X)$, the probability that $T = \tau$ does not depend on the value of X. In other words, when looking at two observations with the same probability (conditional on observable characteristics X) of being exposed to a particular treatment intensity, their treatment intensity is independent of X. That is, the generalized propensity score summarizes all information in the multi-dimensional vector X so that

$$X \quad \perp \quad 1\{T = \tau\}|r(\tau, X). \tag{3}$$

This is a mechanical property of the generalized propensity score, and does not require unconfoundedness. In combination with weak unconfoundedness, the balancing property implies that assignment to treatment is *weakly unconfounded given* *the generalized propensity score*: if assignment to treatment is weakly unconfounded given pre-treatment variables X, then

$$f_T(\tau | r(\tau, X), y(T)) = f_T(\tau | r(\tau, X)) \tag{4}$$

for every τ (see Hirano and Imbens, 2004, for a proof). This result says that we can evaluate the generalized propensity score at a given treatment level by considering the conditional density of the respective treatment level τ. In that sense, we use as many propensity scores as there are treatment levels, but never more than a single score at one treatment level.

We eliminate biases associated with differences in the covariates in two steps (for a proof that the procedure removes bias, see Hirano and Imbens, 2004):

1. Estimate the conditional expectation of per-capita income growth as a function of two scalar variables, the treatment level T and the generalized propensity score R, $\beta(\tau, r) = E[y|T = \tau, R = r]$.

2. Estimate the dose-response function at a particular level of the treatment intensity by averaging this conditional expectation over the generalized propensity score at that particular level of the treatment, $\mu(\tau) = E[\beta(\tau, r(\tau, X))]$.

For the latter, one does not average over the generalized propensity score $R = r(T, X)$, but over the score evaluated at the treatment level of interest, $r(\tau, X)$. In other words, one fixes τ and averages over X_i and $r(\tau, X_i)$ $\forall i$.

3.2 Estimating the generalized propensity score and the balancing of covariates

In the following, we apply the methodology outlined above to our data-set of 2,078 NUTS3 observations receiving different levels of transfers from the European central budget. The treatment of interest, T_i, is the average annual amount of EU transfers relative to the NUTS3 level GDP prior to the beginning of the respective programming period (see Table 1 for a summary of treatment intensities). Following Hirano and Imbens (2004), we assume a normal distribution for the treatment intensity given the covariates:

$$T_i | X_i \sim N(\beta_0 + X_i \beta_1, \sigma^2). \tag{5}$$

where X_i is a column vector and β_1 a row vector. Since the empirical distribution of EU regional transfers per GDP is positively skewed, we chose a logarithmic transformation which, according to the Kolmogorov-Smirnov test (and other conventional test statistics), satisfies the assumption of normality. As determinants of treatment intensity status, we employ the following observables in X_i. First of all, we use log GDP per capita (at Purchasing Power Parity) measured prior to the respective EU budgetary period. This variable should be included, since it is relevant as part of the treatment assignment rule for some types of transfers and/or for the propensity to receive treatment directly from the EU or from the respective NUTS2 administration.[15] To allow for a nonlinear relationship between treatment intensity and log per-capita income, we include a quadratic and a cubic of log GDP per capita along with the main effect. Moreover, we include the Shapley-Shubik (1954) index of a country's voting power prior to a budgetary period to account for effects of power-play and lobbying at the country level. Finally, we include several variables characterizing the economic structure of a region such as log employment, log industrial employment, log service employment, an EU border dummy, and population density (measured as inhabitants per square kilometer) prior to a budgetary period. The economic structure of a region is considered to be a key determinant of regional transfers. Table 2 summarizes moments (such as mean, standard deviation, minimum, and maximum) of the distribution of these variables.

We estimate equation (5) by ordinary least squares as reported in Table 3. Using the observable variables in Table 2 plus a constant, we can explain regional transfer intensity fairly well. According to Table 3, these covariates explain about 56 percent of the variation in treatment intensity. All of the covariates except one, namely an indicator variable identifying regions at the EU border, exert a significant impact on treatment intensity at least at a significance level of 10 percent (using two-tailed test statistics and robust standard errors).

TABLE 3 ABOUT HERE

Building on this estimation, the GPS is calculated as

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} exp\left(-\frac{1}{2\hat{\sigma}^2}(T_i - \hat{\beta}_0 - X_i\hat{\beta}_1)^2\right). \tag{6}$$

As stated above, the GPS allows us to remove any bias in the estimate of the dose-response function, $E[Y_i(\tau)]$, if the covariates are sufficiently balanced. That is, equation (3) has to be satisfied. Furthermore, focusing on the common-support region between treated and control units in the sample is helpful. This avoids perfect predictability of the treatment intensity given a specific value of the GPS. Within the common-support region, units with a certain treatment intensity and respective

[15]NUTS2 regions qualify for Objective 1 transfers if their per-capita GDP falls short of 75 percent of the EU average.

propensity scores have counterparts with similar GPS but different treatment intensity.

In the following, we illustrate that focusing on the common-support region and controlling for the GPS improves comparability of observations with different treatment intensity tremendously in the data at hand.

To assess the performance of the GPS, Hirano and Imbens (2004) suggest to organize the data in groups of treatment intensity. We chose to discretize the treatment intensity according to the quartiles of the distribution which leaves us with four treatment groups. The first and the third group consist of 520 observations, respectively, while the second and fourth group consist of 519 observations, respectively. As is illustrated in Table 4, these groups differ starkly in the observed covariates. The four columns report t-statistics on whether the mean of each covariate in the respective group is significantly different from the mean of the covariates in the three other groups. According to Table 4, only 8 of the 40 t-values are lower than 1.96. Overall, 80 percent of the observables display a significant difference between treated units in a given group and control units with a treatment intensity belonging to another group when using two-tailed test statistics and a 5-percent significance level. The median t-value across all tests is 3.46 and the average mean t-value is 7.76. Accordingly, *ex ante*, the risk of biased causal inference with continuous treatments is particularly large due to such stark differences in observables determining treatment intensity.

TABLE 4 ABOUT HERE

For each treatment group $j \in \{1,2,3,4\}$ we calculate the median treatment intensity T_M^j and evaluate the GPS for the whole sample at median treatment intensities. Hence, we calculate $\hat{R}_i(T_M^j, X_i)$ for each group j and each observation $i = 1, \ldots, N$ using the estimates $\hat{\beta}_0, \hat{\beta}_1', \hat{\sigma}^2$ reported in Table 3. We test the common-support condition by plotting the GPS values $\hat{R}_k(T_M^j, X_k)$ *where* $k \in j$ for observations k being part of group j, against the GPS values $\hat{R}_l(T_M^j, X_l)$ *where* $l \notin j$ of observations l not belonging to group j. Note that both the GPS of observations k and the GPS of observations l are evaluated at the median treatment intensity of group j (T_M^j). Only observations $l \notin j$ featuring GPS values which lie within the range of GPS values of observations $k \in j$ satisfy the common-support condition. Hence, we keep only observation l for which

$$Min\{\hat{R}_k(T_M^j, X_k)\} \leq \hat{R}_l(T_M^j, X_l) \leq Max\{\hat{R}_k(T_M^j, X_k)\} \; \forall j \in \{1,2,3,4\}$$

holds true, where $k \in j$ and $l \notin j$. Put differently, we require each observation to lie within the range of characteristics in each other treatment group.

FIGURE 2 AND 3 ABOUT HERE

These GPS values evaluated at the median treatment intensities of each group are illustrated in Figure 2, where the yellow bars represent observations of group j and the black bars represent all other observations not belonging to j. We display separate histograms for each group $j \in \{1, 2, 3, 4\}$. In the following analysis, we restrict our sample to observations that satisfy the common-support condition. Graphically, this means that we drop observations from the subsample reflected by black bars outside of the range of yellow bars in Figure 2. Obviously, observations that feature dissimilar characteristics to observations in all other groups are mainly located in the outer treatment groups 1 and 4. Geographically, these observations often turn out to be NUTS3 regions in the new member countries of the EU. Figure 3 indicates which NUTS3 regions are inside (in white) or outside of the common-support region in one programming period (in green) or in both of them (in red). When using the GPS to construct comparable units of observation, we find that there are 1,693 of the 2,078 units within the common-support region.

After imposing the common-support condition, we check whether the generalized propensity score achieves a sufficient balancing of covariates and thereby eliminates the selection bias. As explained above, four groups are determined on the basis of the variation in the continuous regional transfer intensity. In addition, we determine 10 blocks *within* each group based on the estimated GPS. We define the blocks for each group $j \in \{1, 2, 3, 4\}$ by the deciles of the GPS evaluated at the median of the group $\hat{R}_k(T_M^j)$ where $k \in j$. Then, we assign each observation $i \in N$ to the respective block according to its GPS evaluated at T_M^j. Note that the blocks are determined for each group separately, and only observations that are part of the respective group are relevant for the calculation of the deciles. By design, the sum of observations over blocks in a group yields the total number of observations in that group.

TABLE 5 ABOUT HERE

Table 5 illustrates the group-and-block structure generated from this algorithm. For instance, the first of the 10 blocks has in total 678 observations of which 40 are located in group 1 and 638 in all other groups. Taking the sum over all blocks and adding the respective group and control observations yields the total number of 1,693 observations in the common-support region. Organization of the data in this way helps to identify comparable observations with the same *predicted* treatment intensity (blocks) but different actual treatment intensity (groups). Following Hirano and Imbens (2004) to test the *balancing property*, we compare observed characteristics of units *within* a specific block of predicted transfer intensity *across* groups of actual treatment intensity. For instance, we compare the 40 observations in cell *group 1/block 1* to the 678 observations in cell *control 1/block 1* and test for equality of covariates. Accordingly, we conduct 10 two-tailed t-tests for *each* group across all covariates. Table 6 reports the mean t-statistics for each group across all covariates, where we weight the t-statistics by the number of observations in order to calculate the mean t-statistic.

TABLE 6 ABOUT HERE

The degree of bias reduction through matching on the GPS is considerable. This can be seen from a comparison of the t-values in Table 6 which contrasts units within the support region *after matching* based on the GPS with the respective ones in Table 4 before matching. While the median and average absolute t-values were 3.46 and 7.79, respectively, in Table 4, the corresponding values in Table 6 are 0.53 and 0.63, respectively. Before matching, almost all t-values were statistically significant while only 2 out of 40 t-values remain marginally significant after adjusting for the GPS.[16] Accordingly, we argue that our generalized propensity score performs well in reducing potential selection bias.

3.3 Estimating the dose-response function

After having largely removed selection bias (into different treatment intensities), we can proceed to estimating and visualizing the relationship between regional transfer intensity and regional GDP growth. To do so, the following "second stage" regression models the conditional expectation of Y_i given T_i and R_i:

$$E[Y_i|T_i, R_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 T_i^3 + \alpha_4 \hat{R}_i + \alpha_5 \hat{R}_i^2 + \alpha_6 \hat{R}_i^3 + \alpha_7 \hat{R}_i T_i \tag{7}$$

using the GPS values estimated in the first stage ($\hat{R}_i$) and the observed treatment intensities (T_i). The parameters are estimated by ordinary least squares, where we implement a blockwise-bootstrap procedure (with 1,000 replications) which takes into account that the GPS is not observed but estimated and that some NUTS3 regions are repeatedly observed. The GPS terms in the regression are the ones "controlling" for selection into treatment intensities. If selectivity indeed matters,

[16] It might be possible to improve the balancing property even further by either using more than 10 blocks or eliminating extreme per-capita income growth rates from the distribution. However, using too many blocks may lead to a small sample bias of the estimates. We have experimented with dropping units with extreme values of per-capita income growth, but this does not have a visible impact on the estimated non-parametric dose-response function. Hence, to avoid small sample bias and an ad-hoc judgment about sample trimming, we decided to use 10 blocks and not drop further observations from the data when assessing the balancing property.

we expect those terms to be statistically significant. In Table 7, we show coefficient estimates from equation 7 and find that all GPS-based polynomial terms matter both individually as well as jointly. Hence, GPS estimation is indeed relevant and significantly reduces the bias of the estimated response of per-capita income growth to changes in regional transfer intensity.

TABLE 7 ABOUT HERE

With the parameters estimated in the second stage, we can now estimate the average potential outcome at treatment level τ, the so-called *dose-response function*:

$$\widehat{E[Y_\tau]} = \frac{1}{N}\sum_{i=1}^{N}[\hat{\alpha}_0+\hat{\alpha}_1\tau+\hat{\alpha}_2\tau^2+\hat{\alpha}_3\tau^3+\hat{\alpha}_4\hat{R}(\tau,X_i)+\hat{\alpha}_5\hat{R}^2(\tau,X_i)+\hat{\alpha}_6\hat{R}^3(\tau,X_i)+\hat{\alpha}_7\hat{R}(\tau,X_i)\tau] \tag{8}$$

In addition to the *dose-response function* itself we display its derivative with respect to the regional transfer intensity – which is commonly referred to as the *treatment effect function*. The latter allows us to infer the *minimum necessary*, the *optimal*, and the *maximum desirable* treatment intensities of EU regional transfers.

4 Results

4.1 Estimates for total EU regional transfers

The dose-response function based on the GPS is a non-parametric estimate of the functional relationship between per-capita income growth and regional transfer intensity, and so is the treatment effect function. Figure 4 displays both the dose-response function and the treatment effect function. In each one of them, we display the nonparametric mean as well as the 95th percentile and the 5th percentile.[17] The graph is obtained for total EU regional transfers at the NUTS3 level under the auspices of the Structural Funds and the Cohesion Fund as in Tables 3-6.

According to the dose-response function in the left panel of Figure 4, the regional per-capita income growth response increases monotonically with regional transfer intensity. For the inter-5-percentile range (i.e., the 90 percent of the observations around the average response), regional transfers generate positive per-capita income growth as intended by the programme. However, a marginal increase of transfer intensity at a given transfer level does not *necessarily* lead to higher per-capita income growth. This can be seen from the derivative of the dose-response function

[17]The two nonparametric loci for the 95th and 5th percentiles are obtained on the basis of the respective values of the bootstrap distribution.

with respect to transfer intensity in the right panel of Figure 4. Since the dose-response function is concave, the treatment effect function declines monotonically. The confidence bands start to include zero per-capita income growth at a treatment intensity of about 1.3 percent. The latter level is indicated by a dashed black line in the treatment effect plot of Figure 4. Below that regional transfer intensity level, an increase in regional transfer intensity leads to an unambiguous increase in the per-capita income growth response. NUTS3 regions with a regional transfer intensity of more than 1.3 percent do no longer unambiguously gain from *additional* EU transfers. In other words, for regions above the 1.3 percent threshold, a reduction of EU transfers to 1.3 percent of their GDP would not necessarily harm their growth prospects.

FIGURE 4 ABOUT HERE

These results point to the existence of a *maximum desirable* level of regional transfers in terms of target region GDP beyond which the per-capita income growth stimulus becomes unimportant so that additional transfers, on average, are wasted. Of all 2,078 observations receiving transfers in the two considered programming periods (this number includes regions within and outside of the common-support region applied in Figure 4), 1,698 have a transfer eligibility below the maximum desirable treatment intensity of 1.3 percent and 380 units are treated in excess of 1.3 percent. The sum of regional transfers to those 380 observations amounted to 148,450.38 mn. Euros. Suppose the European Commission had limited the transfers to those 380 observations to exactly 1.3 percent of their initial GDP. This would correspond to reducing transfers by 32,237.091 mn. Euros in the first programming period and by 31,716.078 mn. Euros in the second programming period. Suppose that the European Commission intended to use those savings of funds in a financially neutral way and spend it in other regions so as to maximize aggregate growth in the Union. Ignoring region size, the Commission would allocate the saved funds to the regions with a low regional transfer intensity. Suppose the funds would be reallocated to the 25 percent of regions with the lowest transfer intensity in the respective programming period. In 1994-99 these were 272 regions featuring an average treatment intensity of about 0.014 percent and in 2000-06 these were 248 regions featuring an average treatment intensity of about 0.026 percent. Moreover, assume that the reallocation was organized so that each of these regions reached the same annual transfer intensity after redistribution.[18] In this case the average treatment intensity could be increased by 0.246 and 0.164 percentage points in the first and in

[18]This kind of reallocation generates the biggest possible effect given the reallocation across regions and ensures that there is no leapfrogging.

the second programming period, respectively.[19] According to our point estimates in Tables 3 and 7 this would boost annual growth in the average region benefiting from this kind of redistribution by about 1.12 percentage points in the first programming period and by about 0.76 percentage points in the second programming period. Since the reduction of transfers to regions above a transfer intensity of 1.3 does not significantly affect their growth rates, this kind of redistribution represents an unambiguous efficiency gain.

Another important concept is the *optimal transfer intensity* which is defined as the threshold where an additional Euro transferred yields exactly one Euro of additional GDP in the recipient region. Accordingly, the optimal transfer intensity has to satisfy the condition

$$\frac{\partial \widehat{E[Y_\tau]}}{\partial \tau}\frac{\partial \tau}{\partial \Im} = ln(GDP+1) - ln(GDP) \;\Leftrightarrow\; \frac{\partial \widehat{E[Y_\tau]}}{\partial \tau} \approx 0.01, \tag{9}$$

where $\Im$ is the absolute level of transfers, $\tau = \frac{\Im}{GDP} \times 100$, and $\frac{\partial \widehat{E[Y_\tau]}}{\partial \tau}$ is the treatment effect function as displayed in the right panel of Figure 4.[20] If the treatment effect function exceeds 0.01, an additional Euro of transfers boosts GDP in the recipient region by more than one Euro such that a higher level of regional redistribution could benefit the Union's total GDP. On the contrary, if the treatment effect function falls short of 0.01, an additional Euro transferred yields less than a Euro in the recipient region such that the volume of transfers is inefficiently high. Note that the recipient region may still significantly benefit from the additional transfer, i.e. the transfer intensity may still be below the maximum desirable transfer intensity. The optimal transfer intensity is indicated by a dashed red line in right panel of Figure 4. Across the two periods under consideration the optimal transfer intensity in Figure 4 amounts to about 0.4 percent of regional GDP.

[19]In the first programming period the first quartile of treatment intensity consists of 272 regions - receiving transfers for 6 years - while in the second programming period it consists of 248 regions - receiving transfers for 7 years. The 272 regions in the first period feature an average GDP of 8,230.146 mn. Euros and receive average annual transfers of 1,504,642 Euros while the 248 regions in the second period feature an average GDP of 10,995.18 mn. Euros and receive average annual transfers of 2,307,696 Euros. Hence, the treatment intensity in those regions that could be reached by redistributing the funds would be $(272 \times 6 \times 1,504,642€ + 32,237.091\text{mn.}€)/(272 \times 6 \times 8,230.146\text{mn.}€) \times 100 = 0.26\%$ and $(248 \times 7 \times 2,307,696€ + 31,716.078\text{mn.}€)/(248 \times 7 \times 10,995.18\text{mn.}€) \times 100 = 0.19\%$ in the first and second programming period, respectively.

[20]Other things equal, an additional Euro boosts the growth rate by $\frac{1}{GDP}$ and the percentage transfer intensity by $\frac{100}{GDP}$ such that the optimal transfer intensity is reached if the estimated treatment effect function $\frac{\partial \widehat{E[Y_\tau]}}{\partial \tau}$ equals 0.01.

While the maximum desirable transfer intensity requires only a significant impact on recipient regions, the optimal transfer intensity requires a transfer multiplier above one. Hence, the latter concept is closely linked to aggregate efficiency. Suppose the European Union's single objective was aggregate growth. Then, the Union should cut transfers to regions with a transfer intensity of more than 0.4 percent (344 and 397 regions in the 1994-99 and 2000-06 programming periods, respectively) and raise transfers to regions below the optimal transfer intensity (741 and 596 regions in the 1994-99 and 2000-06 programming periods, respectively). Yet, such a policy would conflict with the political goal of regional cohesion, since this would imply a reallocation of transfers from less developed regions with a high transfer intensity to rather prosperous regions with a low transfer intensity. Such a trade-off between regional cohesion and aggregate efficiency applies for 162 regions in the 1994-99 period and 199 in the 2000-06 period featuring a transfer intensity above the optimal level but below the maximum desirable level.[21] Cutting transfers to regions beyond the maximum desirable transfer intensity enhances efficiency without harming regional cohesion.

4.2 Estimates for specific treatments

We can produce similar estimates for different sub-components of the EU transfer budget. Since Structural Funds transfers account for the lion's share (about 87 percent on average) of all of the EU's regional transfers, the results for all transfers and Structural Funds transfers alone are very similar. However, we can consider somewhat smaller budgets such as transfers to Objective 1 regions (which account for about 74 percent of all EU-administered regional transfers) and, alternatively, for Cohesion Fund transfers (about 13 percent of total transfers). Again, we can estimate the dose-response function and the treatment effect function.[22]

FIGURE 5 ABOUT HERE

Figures 5 and 6 summarize the results for transfers to Objective 1 regions and Cohesion fund transfers, respectively, akin to Figure 4 for all transfers. Either

[21] Note also that the upper bound of the 95% interval of the optimal treatment intensity is below the maximum desirable treatment intensity. For a theoretical elaboration on the trade-off between aggregate efficiency and regional cohesion see Boldrin and Canova (2001) and Martin (1999).

[22] Obviously, the validity of GPS estimation again depends on balancing of the covariates as with all regional transfers. For the sake of brevity, we suppress the documentation of balancing here, but results are available from the authors upon request. It turns out that the balancing property tests are as successfully met as in the case of all EU regional transfers combined.

one of the two figures displays a similar pattern. First of all, neither the dose-response function nor the treatment effect function is monotonic but hump-shaped. In particular, the confidence bands of the treatment effect function cross the abscissa twice. Hence, the figures suggest that there is a minimum necessary level of transfer treatment in the two sub-categories and a maximum desirable level. However, one reason for the existence of the former is that the number of observations with a very low treatment intensity is relatively small and the variance in response is relatively large for those units. Hence, the statistical evidence of existence of a maximum desirable treatment level is stronger than the one of a minimum necessary one. According to Figures 5 and 6, the maximum desirable treatment threshold is at about 1.8 percent for Objective 1 regional transfers and at about 0.61 percent for Cohesion Fund transfers.

5 Conclusions

This paper focuses on the estimation of the response of average annual GDP per capita growth to changes in the intensity of regional transfers provided by the European Commission under the auspices of the Structural Funds and Cohesion Fund programmes. We use NUTS3 data, the most disaggregated regional data available, covering the two most recent EU budgetary periods – 1994-99 and 2000-06. Non-parametric generalized propensity score analysis allows us to estimate the causal effect of different levels of EU transfers on GDP growth.

Our results point to an optimal transfer intensity of 0.4 percent of target region GDP and a maximum desirable intensity of 1.3 percent. Transfers to regions below a transfer intensity of 0.4 percent enhance aggregate efficiency as they exhibit a multiplier above one. Regions with EU transfer intensity below 1.3 percent of their beginning-of-period GDP could grow faster by further EU transfers. Regions with a transfer intensity of more than 1.3 percent of GDP could give up EU transfers without experiencing a significant drop in their average annual per-capita income growth rate. For a certain range of transfer intensities, we detect a trade-off between aggregate efficiency and regional cohesion. Reducing the transfers to regions below the maximum desirable transfer intensity significantly harms their growth prospects but may enhance aggregate efficiency, if the transfer intensity was above the optimal level.

Redistribution of EU transfers from the 18 percent of regions that receive more than 1.3 percent of initial GDP as EU transfers to regions below that threshold would be efficient and could boost regional convergence.

References

Becker, Sascha O., Peter H. Egger, and Maximilian von Ehrlich, "Going NUTS: The Effect of EU Structural Funds on Regional Performance," *Journal of Public Economics*, 2010, *94* (9-10), 578–590.

_ , _ , _ , and Robert Fenge, "Going NUTS: The Effect of EU Structural Funds on Regional Performance," *CESifo Working Paper No. 2495*, November 2008.

Boldrin, Michele and Fabio Canova, "Europe's Regions - Income Disparities and Regional Policies," *Economic Policy*, 2001, *32*, 207–253.

Dehejia, Rajeev and Sadek Wahba, "Causal effects in nonexperimental studies: reevaluating the evaluation of training programs," *Journal of the American Statistical Association*, 1999, *94* (448), 1053–1062.

European Commission, "ERDF in Figures 1988," Brussels: Commission of the European Communities, 1989.

_ , "Regional Policy – Inforegio," `http://ec.europa.eu/regional_policy/policy/fonds/index_en.htm` 2008.

Felsenthal, Dan and Moshé Machover, "The Weighted Voting Rule in the EU's Council of Ministers, 1958-95: Intentions and Outcomes," *Electoral Studies*, 1998, *16*, 33–47.

Hagen, Tobias and Philipp Mohl, "Which is the Right Dose of EU Cohesion Policy for Economic Growth?," *ZEW Discussion Paper No. 08-104*, December 2008.

Heckman, James J., Hidehiko Ichimura, and Petra Todd, "Matching as an econometric evaluation estimator: evidence from evaluating a job training programme," *Review of Economic Studies*, 1997, *64* (4), 605–654.

Hirano, Keisuke and Guido W. Imbens, "The propensity score with continuous treatments," in Andrew Gelman and Xiao-Li Meng, eds., *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives*, Wiley, 2004, chapter 7.

Hirshleifer, Jack, "On the Theory of Optimal Investment Decision," *Journal of Political Economy*, 1958, *66* (4), 329–352.

Imai, Kosuke and David A. Van Dijk, "Causal Inference with General Treatment Regimes: Generalizing the Propensity Score," *Journal of the American Statistical Association*, 2004, *99* (467), 854–866.

Imbens, Guido W., "The Role of the Propensity Score in Estimating Dose-Response Functions," *Biometrika*, 2000, *87* (3), 706–710.

Martin, Philippe, "Public Policies, Regional Inequalities and Growth," *Journal of Public Economics*, 1999, *73*, 85–105.

Murphy, Kevin M., Andrei Shleifer, and Robert M. Vishny, "Industrialization and the Big Push," *Quarterly Journal of Economics*, 1989, *106*, 503–530.

Rosenbaum, P.R. and D.B. Rubin, "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 1983, *70*, 41–55.

Sachs, Jeffrey D., John W. McArthur, Guido Schmidt-Traub, Margaret Kruk, Chandrika Bahadur, Michael Faye, and Gordon McCord, "Ending Africa's Poverty Trap," *Brookings Papers on Economic Activity*, 2004, *2004*, 117–216.

Shapley, Lloyd S. and Martin Shubik, "A Method for Evaluating the Distribution of Power in a Committee System," *American Political Science Review*, 1954, *48*, 787–792.

Widgren, Mika, "The Impact of Council Voting Rules on EU Decision-Making," *CESifo Economic Studies*, 2009, *55*, 30–56.

Table 1: EU Regional Transfers and GDP per Capita Growth in NUTS3 Regions

	Mean	Std. dev.	Min	Max	Treated obs.
Annual transfers per treated region					
Total EU transfers (1,000 Euros)	23,140.840	49,744.110	5.345	778,531.000	2,078
Objective 1 transfers (1,000 Euros)	52,130.820	68,868.490	602.694	778,531.000	702
Cohesion Fund transfers (1,000 Euros)	21,479.040	36,090.000	17.878	334,935.200	363
Total EU transfers/GDP (%)	.759	1.512	.00009	29.057	2,078
Objective 1 transfers/GDP (%)	1.991	2.103	.076	29.057	702
Cohesion Fund transfers/GDP(%)	.659	.950	.002	6.338	363
Annual GDP per capita growth	.042	.017	-.039	.138	2,078

Notes: Our pooled sample consists of 1,091 EU15 NUTS3 regions in the 1994-99 programming period and 1,213 EU25 NUTS3 regions in the 2000-06 programming period. We miss information on the four French overseas-departéments and the two autonomous Portuguese regions Madeira and Azores for both periods. In the second period we loose 12 regions that cannot be assigned to the 1994-99 data due to a territorial reform in Saxony-Anhalt. Hence, in total we have 2,292 treated and untreated observations. In order to obtain annual transfers per GDP we divide the annual transfers with the GDP prior to the start of the respective programming period. This is 1993 for the EU12 in the first period but 1994 for the countries joining in 1995 (Austria, Finland, and Sweden), and 1999 for the EU15 in the second period but 2003 for the accession countries of 2004. Moreover, we adjust for the number of years the respective countries actually received funds. This is 6 years for the EU12 in the first period and 5 years for the countries joining in 1995, and 7 years for the EU15 but 3 years for the new accession countries of 2004 in the second period.

Table 2: Descriptive Statistics

	Mean	Std. dev.	Min	Max
	(1)	(2)	(3)	(4)
GDP per capita	9.583	.367	8.068	11.038
(GDP per capita)^2	91.971	7.024	65.098	121.835
(GDP per capita)^3	883.945	101.057	525.232	1344.806
Shapley-Shubik index	.09	.041	0	.134
Budgetary period dummy	.478	.5	0	1
Border region dummy	.249	.433	0	1
Employment	4.567	.919	.331	7.712
Industrial employment	3.286	1.009	-2.765	6.603
Service employment	4.075	.976	.32	7.427
Population density	.448	.957	.002	20.381
Observations	2,078			

Notes: Annual GDP per capita growth is measured at PPP where we use logarithmic growth rates between 1993 and 1999 for the first period, and growth rates between 1999 and 2006 for the second period. Time varying covariates as per capita GDP (PPP), employment measures etc. refer to initial values, i.e. 1993 for the first period and 1999 for the second period. Total employment, industrial employment, service employment, and per capita GDP are measured in logarithmic terms. We miss information on the four French overseas-departéments and the two autonomous Portuguese regions Madeira and Azores for both periods. In the second period we loose 12 regions that cannot be assigned to the 1994-99 data due to a territorial reform in Saxony-Anhalt.

Table 3: Estimation of the Generalized Propensity Score (GPS)

	Coef.	Std. err.	
GDP per capita	403.226	55.040	***
(GDP per capita)^2	-42.016	5.787	***
(GDP per capita)^3	1.443	.203	***
Shapley-Shubik index	-4.903	.809	***
Period	.672	.063	***
Border region	-.054	.067	
Employment	1.964	.278	***
Industrial employment	-.957	.107	***
Service employment	-.867	.197	***
Population density	.055	.029	*
Constant	-1,284.350	174.267	***
Observations	2078		
R^2	.561		

Notes: ***, **, * denote significance at the 1, 5, and 10% level, respectively.

Table 4: Treatment Groups and Covariates

	Group 1	Group 2	Group 3	Group 4
GDP per capita	**-22.942**	**-9.585**	**2.803**	**33.683**
(GDP per capita)^2	**-23.220**	**-9.339**	**3.107**	**33.041**
(GDP per capita)^3	**-23.462**	**-9.074**	**3.402**	**32.348**
Shapley-Shubik index	**-6.211**	**-3.286**	**2.932**	**6.575**
Budgetary period dummy	**2.384**	.103	-1.674	-.810
Border region dummy	**3.123**	1.333	-1.097	**-3.361**
Employment	**-5.649**	**-2.473**	**3.316**	**4.796**
Industrial employment	**-7.915**	**-3.464**	**3.463**	**7.919**
Service employment	**-6.053**	**-3.353**	1.757	**7.699**
Population density	**-6.906**	-.548	.606	**6.850**
Observations	520	519	520	519
Median t-value	**3.46**			
Mean t-value	**7.79**			

Notes: The groups are generated according to the quartiles of total EU transfers per GDP. t-values reported in bold face indicate significance at the 5% level.

Table 5: Cell size for comparison of treated and control units in the matrix of 10 blocks and 4 groups

Block	Group 1	Control 1	Group 2	Control 2	Group 3	Control 3	Group 4	Control 4
1	40	638	49	398	49	336	31	848
2	42	183	47	155	49	183	31	256
3	41	114	48	113	49	121	32	102
4	40	91	50	105	49	147	32	56
5	41	73	48	99	49	73	30	30
6	40	57	47	98	49	63	32	29
7	41	53	50	49	49	89	32	20
8	41	30	48	74	49	52	31	15
9	41	27	48	67	49	67	31	11
10	40	20	48	52	49	72	31	13

Notes: The figures in the table refer to the number of observations in a treatment (or respective control) group and a specific generalized propensity score block.

Table 6: Balance of Covariates accounting for the GPS

	Group 1	Group 2	Group 3	Group 4
GDP per capita	-.474	**-1.989**	-1.039	1.006
(GDP per capita)^2	-.462	**-1.961**	-1.001	.981
(GDP per capita)^3	-.451	-1.932	-.962	.956
Shapley-Shubik index	-.017	-.182	.728	-.522
Budgetary period dummy	.547	-.530	-.828	.120
Border region dummy	.606	-.104	-.283	1.253
Employment	.448	-.096	.383	.486
Industrial employment	.219	-.099	.774	.687
Service employment	.405	-.171	.059	.680
Population density	.124	-.317	-.835	.558
Observations	407	483	490	313
Median t-value	.53			
Mean t-value	.63			

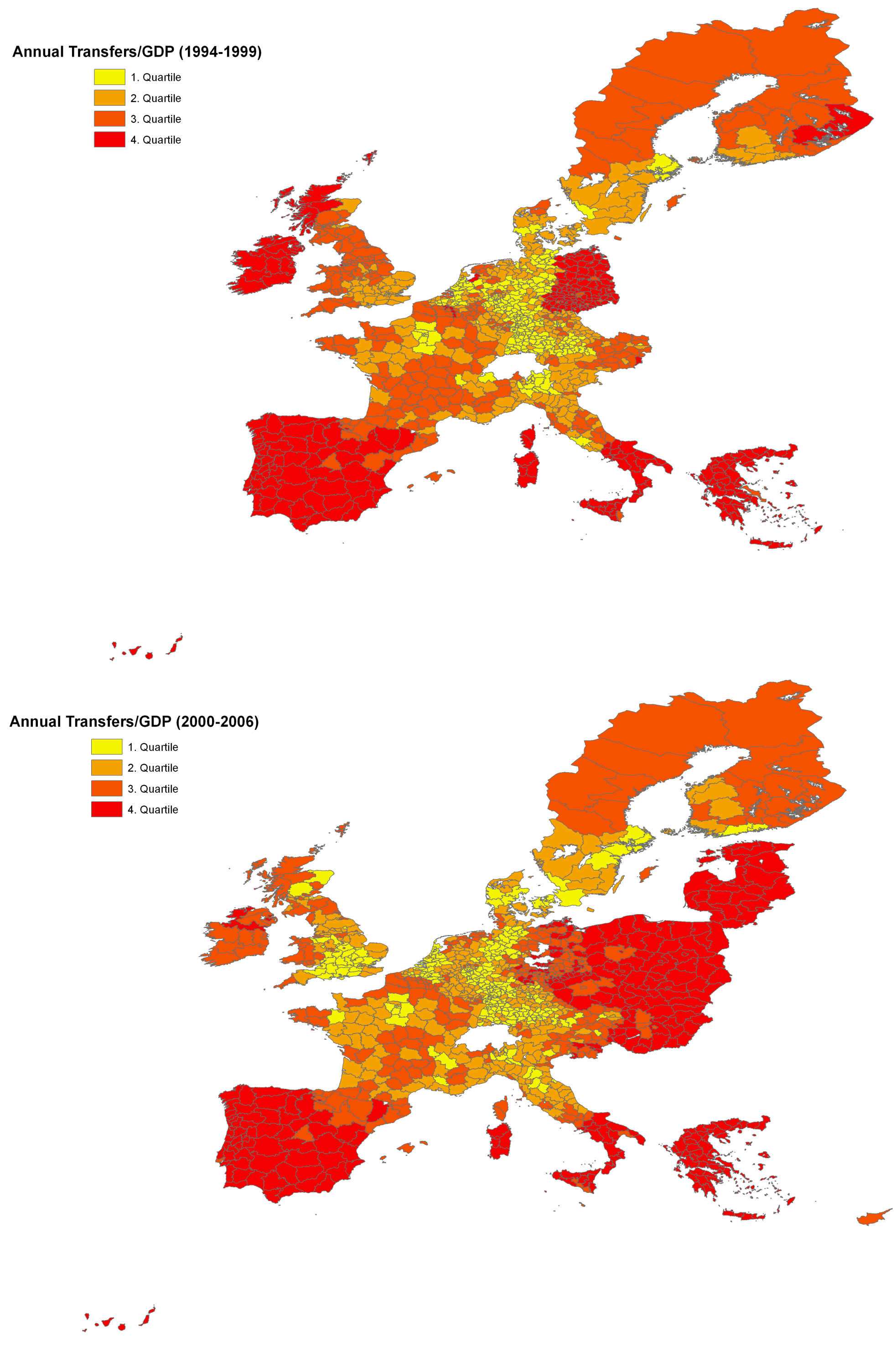
Notes: The groups are generated according to the quartiles of total EU transfers per GDP. Observations which do not satisfy the common support condition are excluded from the respective groups. In order to account for the GPS values we discretize the GPS values at 10% bandwidth. t-values reported in bold face indicate significance at the 5% level.

Table 7: Estimation of the Dose-Response Function

	Coef.	Std. err.
ln(Total EU transfers/GDP)	.012	.0007 ***
ln(Total EU transfers/GDP)^2	.001	.0001 ***
ln(Total EU transfers/GDP)^3	.00004	4.61e-06 ***
ln(GPS)	.001	.0002 ***
ln(GPS)^2	.0005	.00006 ***
ln(GPS)^3	.00003	3.89e-06 ***
ln(GPS)*ln(Fund/GDP)	9.00e-06	.00003
Constant	.084	.002 ***
Observations	1,693	
R^2	.11	

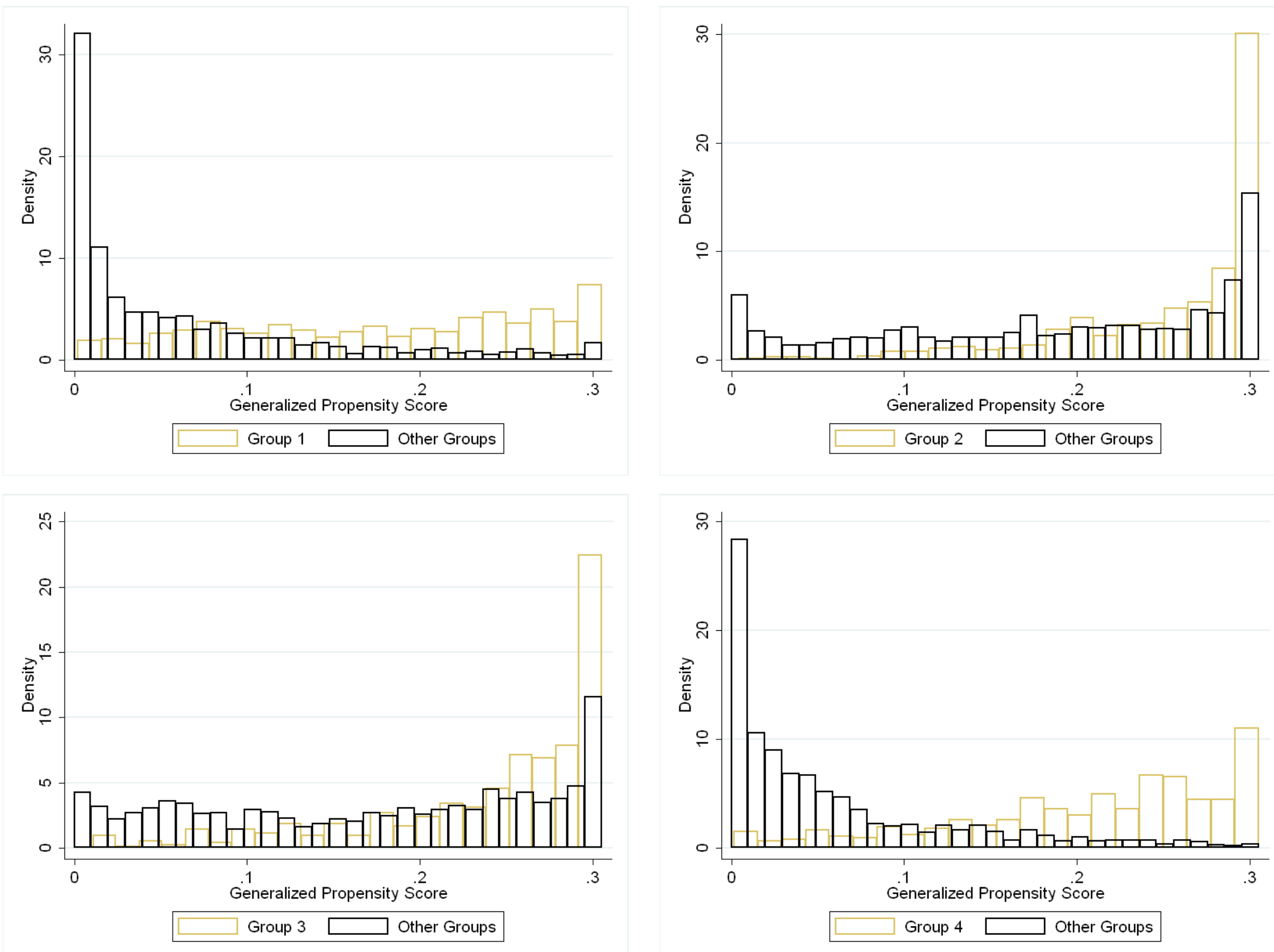
Notes: ***, **, * denote significance at the 1, 5, and 10% level, respectively. We estimate the dose-response function by blockwise bootstrapping (i.e. drawing from the regional level and then merging respective periods) with 1,000 iterations that take into account first-stage estimations.

Figure 1: Regional Distribution of EU Transfers



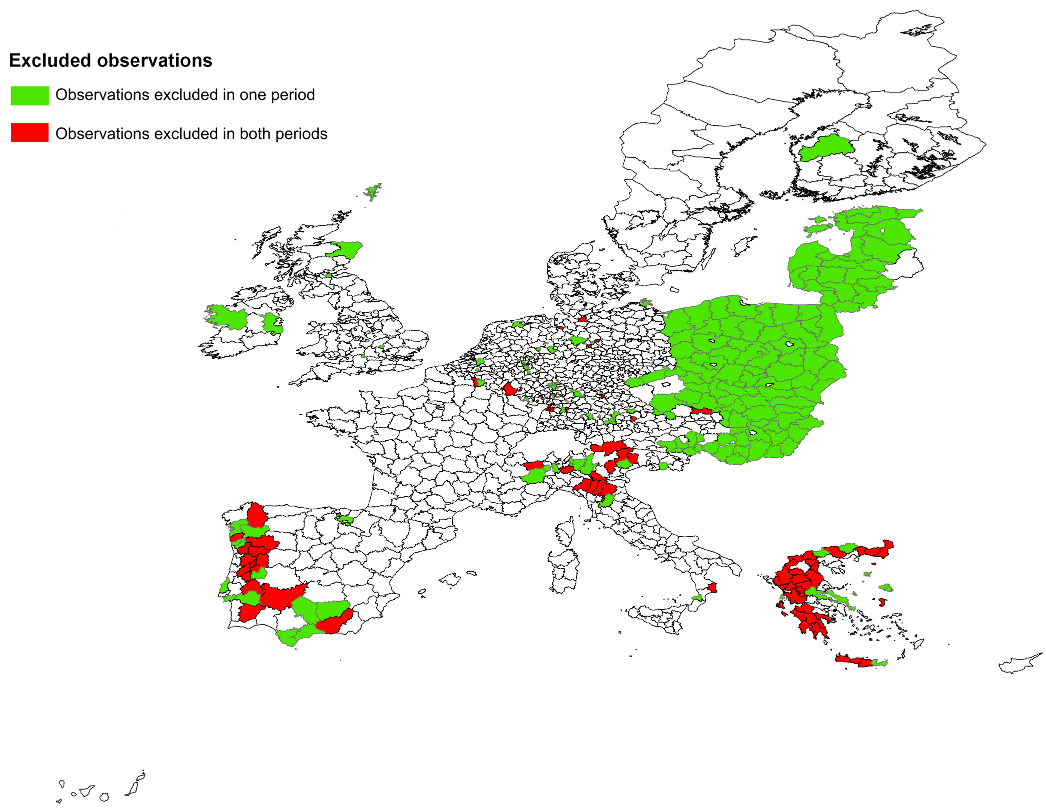
Note: The maps indicate the annual transfer intensity (total EU transfers per GPD) for the 1994-99 and 2000-06 programming periods.

Figure 2: Common Support of the Generalized Propensity Score



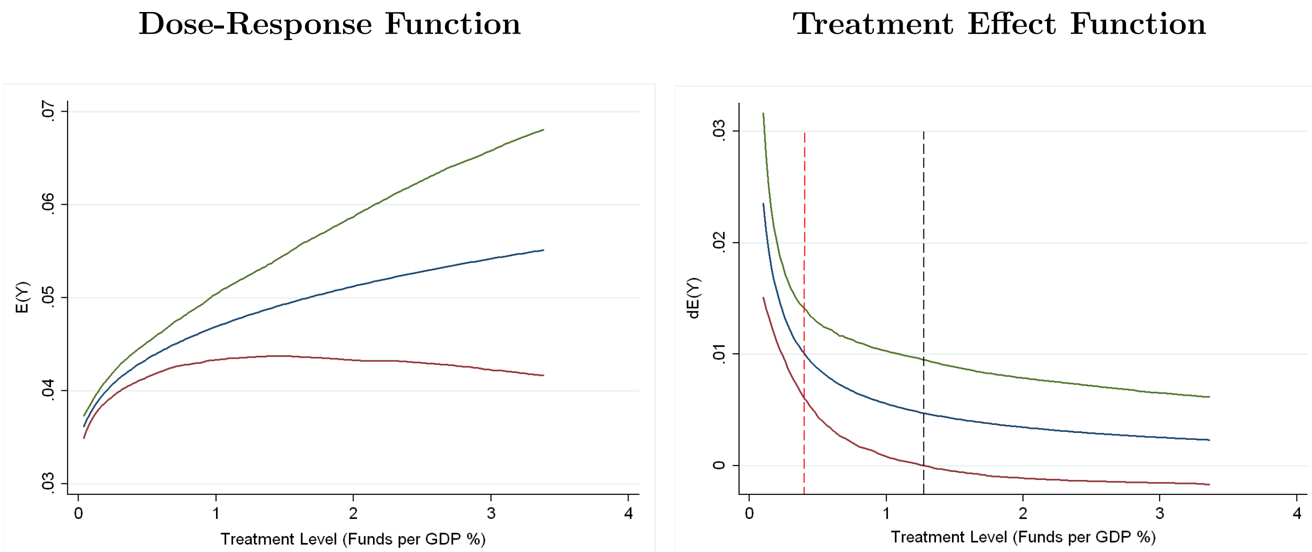
Note: The groups are generated according to the quartiles of total EU transfers per GDP.

Figure 3: Observations failing common support restriction



Note: The maps indicate the region-period observations that are dropped due to their GPS values lying outside the common support region.

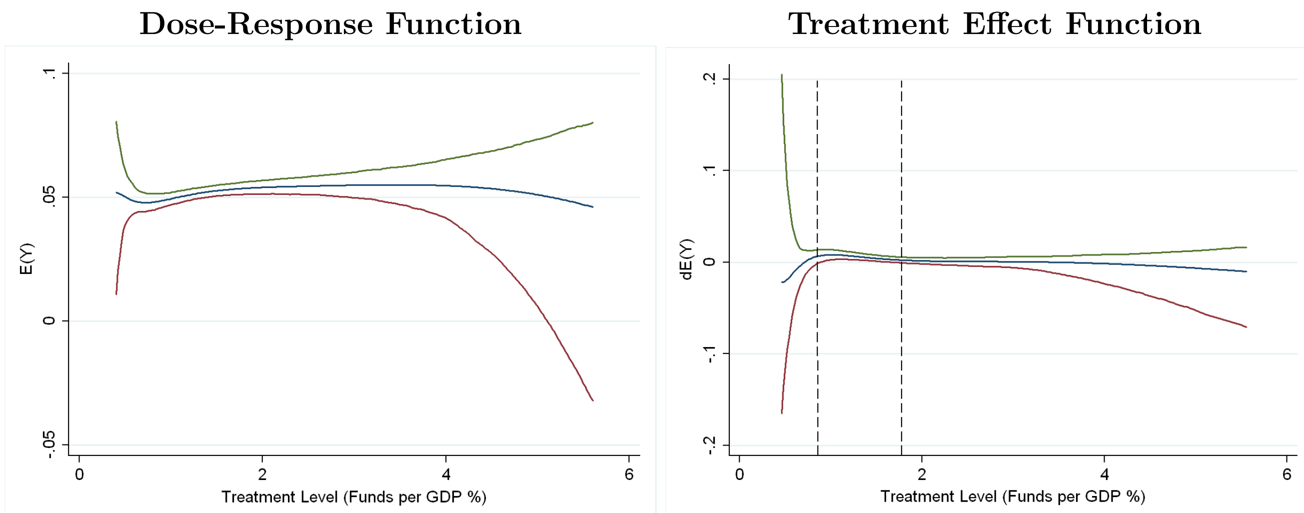
Figure 4: Effects of Total EU Transfers



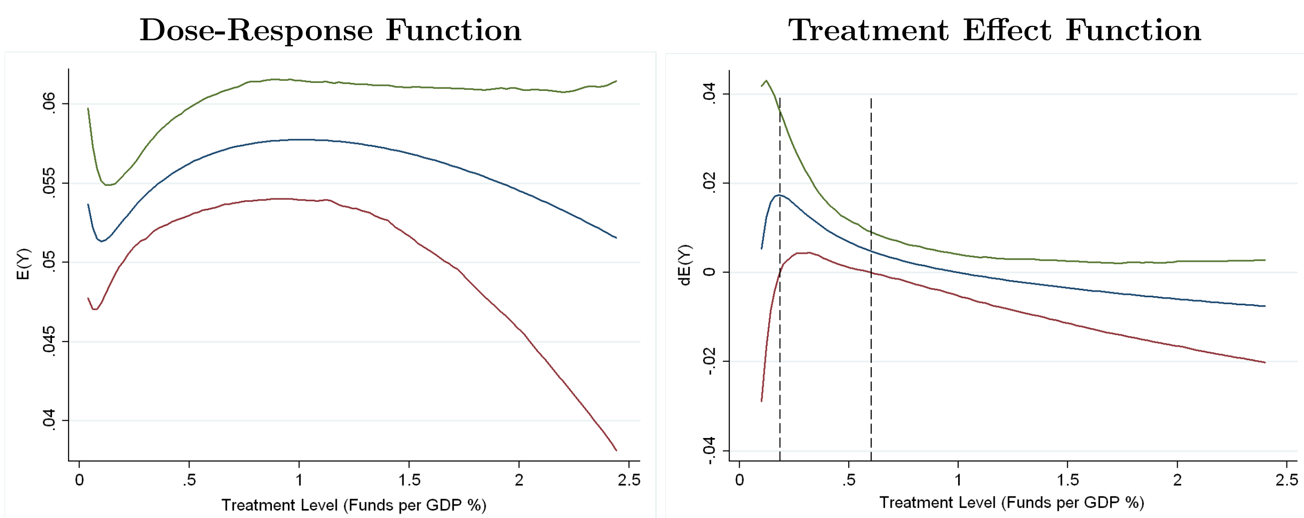
Note: Observations with treatment level in the highest and lowest 5% are trimmed. The black dashed bar indicates the maximum desirable treatment intensity, the red dashed bar indicates the optimal treatment intensity.

Figure 5: Effects of Objective 1 and Cohesion Fund Transfers

A. Objective 1



B. Cohesion Fund



Note: Observations with treatment level in the highest and lowest 5% are trimmed. The black bars indicate the minimum necessary and the maximum desirable treatment intensities.