Going NUTS: The Effect of EU Structural Funds on Regional Performance*

Sascha O. Becker
U Stirling, ifo, CESifo and IZA

Peter H. Egger
ETH Zurich, CEPR, and CESifo

Maximilian von Ehrlich
LMU Munich

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Abstract

The European Union (EU) provides grants to disadvantaged regions of member states to allow them to catch up with the EU average. Under the Objective 1 scheme, NUTS2 regions with a per-capita GDP level below 75% of the EU average qualify for structural funds transfers from the central EU budget. This rule gives rise to a regression-discontinuity design that exploits the discrete jump in the probability of EU transfer receipt at the 75% threshold for identification of causal effects of Objective 1 treatment on outcome such as economic growth of EU regions. We find positive per-capita GDP growth effects of Objective 1 transfers, but no employment growth effects.

Keywords: Structural funds; Regional growth; Regression-discontinuity design; Quasi-randomized experiment

JEL Classification: C21; O40; H54; R11

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E-mail addresses: sascha.becker@stir.ac.uk; egger@kof.ethz.ch; vonEhrlich@lmu.de.

1 Introduction

Most federations – national or supra-national in scope – rely on a system of fiscal federalism which allows for transfers across jurisdictions. Examples of such national federations are the United States of America or the German States (Länder). An example of a supra-national federation is the European Union (EU). The most important aim of the aforementioned transfers is to establish equalization – at least partially – of fiscal capacity and per-capita income among the participating jurisdictions (see Ma, 1997).

In comparison to other federations, the magnitude of equalization transfers is particularly large within the EU. The lion's share of the EU's fiscal equalization transfers is spent under the auspices of the *Structural Funds Programme*. Starting in 1988, this programme distinguishes between transfers under three mutually exclusive schemes: Objective 1, Objective 2, and Objective 3.

The goal of our study is to assess the causal effect of Objective 1 status on per-capita GDP growth of treated regions in the EU, using a regression-discontinuity design for program evaluation. Our analysis sheds light on the effectiveness of the Objective 1 scheme (i.e., whether it causes treated regions to grow faster than control regions) and its net benefits (i.e., whether the growth induced justifies the costs incurred).

We confine our analysis to Objective 1 treatment for three reasons. First, Objective 1 funding has the explicit aim of fostering GDP-per-capita growth in regions that are lagging behind the EU average and of promoting aggregate growth in the EU (European Commission, 2001). Second, Objective 1 expenditures form the largest part of the overall *Structural Funds Programme* budget. They account for more than two thirds of the programme's total budget: 70% in the 1988-93 period, 68% in the 1994-99 period and 72% in the 2000-06 period (see European Commission, 1997, p. 154f., and European Commission, 2007, p. 202). Third, the Objective 1 scheme has been largely unchanged over all three programming periods of its existence.[1]

[1]Objective 2 covers regions that face socioeconomic problems which are mainly defined by high unemployment rates. More precisely, regions must satisfy three criteria to be eligible for Objective 2 transfers: first, an unemployment rate above the Community average; second, a higher percentage of jobs in the industrial sector than the Community average; and, third, a decline in industrial employment. Objective 3 deals with the promotion of human capital. The main goal is the support of the adaptation and modernization of education, training and employment policies in regions. Objectives 2 and 3 were modified slightly over the programming periods considered here. In 1989-93 and 1994-99 three additional objectives of minor importance existed which were abolished in 2000-06. For the new programming period 2007-13, Objectives 1, 2, and 3 have been renamed Convergence Objective, Regional Competitiveness and Employment Objective, and European Territorial Co-operation Objective.

A region qualifies for Objective 1 transfers if its GDP per capita in purchasing power parity terms (PPP) is less than 75% of the EU average. For the programming periods 1989-93, 1994-99, and 2000-06, the European Commission computed the relevant threshold of GDP per capita in PPP terms based on the figures for the last three years of data available at the time when the Commission's regulations came out.

To further understand the Objective 1 scheme, it is useful to introduce the classification system of regional units in the EU. Eurostat, the statistical office of the European Commission, distinguishes between three sub-national regional aggregates: NUTS1 (large regions with a population of 3-7 million inhabitants); NUTS2 (groups of counties and unitary authorities with a population of 0.8-3 million inhabitants); and NUTS3 regions (counties of 150-800 thousand inhabitants).[2]

With a few exceptions, transfer eligibility is determined at the NUTS2 level and in advance for a whole programming period of several years.[3] For instance, in the 1994-99 programming period, the European Commission provided Objective 1 transfers to 64 out of 215 NUTS2 regions in the EU15 area. A graphical illustration of the regions receiving Objective 1 funds ("treated regions") across the three most recent budgetary periods is provided in Figure 1.

Figure 1 and Table 1 about here

The amounts paid are quite significant for the recipient NUTS2 regions. In the three most recent programming periods, the Objective 1 treated regions received on average transfers in the order of 1.4%, 1.8% and 1.1% of their GDP (see European Commission, 1997, 2007; Table 1 provides further information). A number of questions relating to these expenses are of obvious interest to both policy makers and

[2]NUTS is the acronym for *N*omenclature des *U*nités *T*erritoriales *S*tatistiques coined by Eurostat. The highest level of regional aggregation (NUTS1) corresponds to Germany's *Bundesländer*, France's *Zones d'Études et d'Aménagement du Territoire*, the United Kingdom's *Regions of England/Scotland/Wales* or Spain's *Grupos de Comunidades Autónomas*. At the other end of the NUTS classification scheme, NUTS3 regions correspond to *Landkreise* in Germany, to *Départements* in France, to *Unitary Authorities* in the UK or to *Comunidades Autónomas* in Spain.

[3]Owing to their territorial adjacency to Belgium's Objective 1 region Hainaut, the three French préfectures Valenciennes, Douai, and Avesnes (within the NUTS3 region Nord) received Objective 1 status in the 1994-99 programming period even though their NUTS2 mother region Nord-Pas-de-Calais did not qualify. The Austrian region Burgenland as the single Objective 1 region of the 1995 accession countries (Austria, Finland, and Sweden) did only receive Objective 1 funds from 1995 onwards. Similarly, the Objective 1 regions of the 2004 accession countries (Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, and Slovak Republic, and Slovenia) did only receive funds from 2004 onwards.

economists. *To which extent do economic outcomes in the recipient regions actually respond to such re-distributional transfers?* This calls for an evaluation of the overall (causal) impact of transfers. Moreover, one could ask about the net benefits of transfers: *Does the response in economic outcomes in the treated regions justify the size of the programme and, in particular, its costs to the untreated jurisdictions?* Surprisingly little is known to answer these questions.

A small number of previous studies looked into the impact of re-distributional regional policies on economic outcomes (see section 2 for a detailed discussion of the literature). Most of that research focused on the impact of the EU's *Structural Funds Programme*. Yet, essentially all existing work on that topic uses fairly aggregated regional data at the NUTS1 level. Whereas some papers even used NUTS2-level data, they did not exploit important features of the design of the programme. This might be problematic because, by design of the programme, regions which are eligible for transfer payments under Objective 1 ("poor regions") differ systematically on average from non-eligible ones ("rich regions"). Furthermore, with regard to transfers under the auspices of the *Structural Funds Programme*, most papers use cross-sectional data. Hence, the level of aggregation, the cross-sectional nature of the data employed, and the type of empirical methods applied in previous work rendered identification of the causal effect of the programme difficult if not impossible.

We compile data on 285 NUTS2 and 1,213 NUTS3 regions in Europe for three programming periods – 1989-93, 1994-99, and 2000-06 – to assess the causal effect of transfers through the EU's *Structural Funds Programme* on economic outcomes such as average annual growth of GDP per capita and of employment of treated versus untreated regions. Ideally, in an experimental setting, we would randomly assign regions to a treatment and control group, i.e., give structural funds to some randomly selected regions and compare their economic outcomes to those of randomly selected control regions. While such an ideal experiment is not possible, the EU criteria for assigning Objective 1 status have quasi-experimental features. The 75% threshold at the NUTS2 level gives rise to a regression-discontinuity design (RDD) whereby regions in the vicinity of that threshold are likely to be very similar ex ante, but those below the 75% threshold qualify for Objective 1 funds, whereas those above do not.

The 75% assignment rule is strictly applied in the vast majority of cases: for 628 out of the 674 NUTS2 observations across all periods, Objective 1 status complies with the formal 75%-rule (see below for further details on exceptions from the rule). However, parial noncompliance with the 75% rule brings us to a *fuzzy* RDD.[4] We analyze causal effects on growth of per-capita GDP at purchasing power parity

[4]Eligibility is synonymous with actual treatment under sharp RDD but not under fuzzy RDD.

(PPP) at the NUTS2 level for most of the paper, but also at the NUTS3 level since part of the fuzziness in the design is brought about by exceptions below the NUTS2 level. Similarly, we consider possible effects on employment. Finally, we deliver a back-of-the-envelope calculation of the net benefits of the programme.

Overall, we identify positive causal effects of Objective 1 treatment on the growth of per-capita income at PPP. In the benchmark specification and procedure, we estimate a differential impact of Objective 1 programme participation on the growth of GDP per capita at PPP of about 1.6 percentage points within the same programming period. No such effects can be found for employment growth. A back-of-the envelope calculation, based on the benchmark specification, suggests that – on average – the funds spent on Objective 1 have a return which is about 1.20 times their costs in terms of GDP. Hence, the programme seems to be effective *and* generates benefits in the recipient regions which exceed the costs to the EU budget.

The remainder of the paper is organized as follows. The next section provides a discussion of the state of the literature on the evaluation of the EU's *Structural Funds Programme*. Section 3 presents our data and shows descriptives on treated (i.e., Objective 1) and untreated (i.e., non-Objective 1) NUTS2 and NUTS3 regions. Section 4 summarizes the findings about the (causal) effects of Objective 1 treatment on the growth of GDP per capita when using the aforementioned quasi-experimental design. Section 5 provides sensitivity checks, extensions, and a back-of-the-envelope calculation of the net benefits of the European Union's Objective 1 Programme based on the benchmark estimates of the treatment effect. The last section concludes with a summary of the most important findings.

2 Effects of the Structural Funds Programme: state of the debate

The interest in effects of the EU's structural policy roots in empirical work on regional growth and convergence. Sala-i-Martin (1996) started the debate by diagnosing a failure of the EU's structural policy based on cross-sectional regressions showing that the regional growth and convergence pattern in the EU was not different from the one in other federations which lack a similarly extensive cohesion programme. Obviously, such a conclusion requires comparability of federations and their regions in all other respects, which is not necessarily the case. However, Boldrin and Canova (2001) came to similar conclusions as Sala-i-Martin (1996) when focusing on regional growth within the EU and comparing recipient and non-recipient regions. Yet, both papers looked at the combined *Structural Funds Programme* and not specifically at the Objective 1 scheme, which primarily aims at closing the gap in per-capita income. Furthermore, they used fairly aggregated NUTS1 and NUTS2 data, since data at the NUTS3 level was not available at the time.

This evidence is different from the findings of Midelfart-Knarvik and Overman (2002) who identify a positive impact of the *Structural Funds Programme* on industry location and agglomeration at the national level.[5] Similarly, Beugelsdijk and Eijffinger (2005) and Ederveen, de Groot and Nahuis (2006) took a national perspective and found a positive relationship between *Structural Funds Programme* spending and GDP-per-capita growth (at least, in countries with favorable institutions). At the sub-national (NUTS1 or NUTS2) level, Cappelen, Castellacci, Fagerberg and Verspagen (2003) as well as Ederveen, Gorter, de Mooij and Nahuis (2002) detect a significant positive impact of structural funds on regional growth while Dall'erba and Le Gallo (2008) do not support this conclusion.

However, as argued in the introduction, there is a number of potential problems with evaluations in earlier work which mostly relate to the limited availability of sufficient data in the cross-sectional as well as the time dimensions, and to the methods applied.[6] With much more data at hand now, we may revisit earlier conclusions and estimate causal effects of Objective 1 treatment of regions by means of a regression-discontinuity design.[7]

3 Data and descriptive statistics

3.1 Data sources

For the empirical analysis, we link data from several sources. Our main outcome variable of interest is average annual growth of GDP per capita at purchasing power

[5]However, they find that the funds seem to stimulate economic activity counter to the comparative advantage of the recipient countries.

[6]In many of the previous studies, the number of observations and, hence, the number of treated and untreated regions, is so small that it almost precludes the use of modern techniques for program evaluation, such as our regression-discontinuity design.

[7]A related approach of identifying causal effects of regional policy for one selected EU country is conducted in Criscuolo, Martin, Overman and van Reenen (2009). They use firm-level data for the United Kingdom (UK) and employ a quasi-experimental framework to identify the causal effects of the UK's *Regional Selective Assistance* programme on firm performance. They generate an instrument for recipient status of state aid by exploiting changes in the area-specific eligibility criteria. The eligibility criteria in the UK are determined by the European Commission's guidelines for regional development policies which also underly the *Structural Funds Programme*. The revision of regional eligibility for structural funds before each programming period also determines the provision of *Regional Selective Assistance* to firms in the UK and may therefore be used as an exogenous instrument. The authors find a significant positive effect of state aid on investment as well as on employment.

parity (PPP) during a programming period. As an alternative outcome, we look at average annual employment growth. Data for these variables at the NUTS2 and NUTS3 regional levels are taken from Cambridge Econometrics' Regional Database. Data on Objective 1 treatment and the amount of funds under the *Structural Funds Programme* at various levels of regional aggregation were collected from documents of the European Commission concerning structural funds.[8]

In part of our analysis, we use information on sectoral employment, population, and investment as control variables at the level of NUTS2 and NUTS3 regions from Cambridge Econometrics' Regional Database.

Moreover, some of the sensitivity checks involve data on the geographical size and location of regions from the Geographic Information System of the European Commission (GISCO). We use this information to guard against a possible bias of the Objective 1 treatment effect associated with spillovers across regional borders.

Finally, some of the empirical models in the sensitivity analysis involve a measure of countries' voting power in the EU Council (measured by the Shapley and Shubik (1954) index). Those are taken from Felsenthal and Machover (1998) for the years until 2004 (for EU12 and EU15), and from Widgrén (2009) for the current voting scheme in the EU27 under the rules of the Treaty of Nice.

3.2 Descriptive statistics

It is instructive to consider the variation in GDP per capita across NUTS2 jurisdictions in the EU. This is done in Table 2 for the year 1999 (i.e., the year prior to the last available programming period, 2000-06).

Table 2 about here

The number of countries considered in the table is 25. Between 1986 and 1995, the EU consisted of 12 economies as included in the programming period 1989-93. Countries that joined the EU in 1995 (Austria, Finland, and Sweden) were included in the EU regulations for the programming period 1994-99. Similarly, the

[8]For each programming period, eligibility was determined by the European Commission one year in advance of the beginning of the programming period on the basis of the figures for the last three years of data that were available at the time. Concerning the programming period 1989-93, see Council Regulation number 2052/88 and – regarding the New German Länder – see Official Journal L 114, 07/05/1991. The NUTS2 regions covered by Objective 1 in 1994-99 are listed in Council Regulation 2081/93 and – regarding the new member states Austria, Finland, and Sweden – in the Official Journal L 001, 01/01/1995. For the programming period 2000-06, data stem from Council Regulation 502/1999 and – for the new member countries of 2004 – from the Official Journal L 236, 23/09/2003. All the regulations are available through the database for European Law, EUR-Lex.

Eastern Enlargement of the European Union (in 2004) by 10 economies[9] matters for the programming period 2000-06. Table 2 sheds light on the variation of GDP per capita across NUTS2 regions between and within countries and relative to the average GDP of EU25 countries, using data from the year 1999.

We may summarize insights from that exercise as follows. There is considerable variation in GDP per capita both between and within EU countries. The former obviously strongly increased after the EU's enlargement in 2004. Some countries host NUTS2 regions above and below the 75% threshold.

According to the 75%-rule, *all* NUTS2 regions in a country would be eligible for Objective 1 transfers if the maximum GDP per capita across all regions were smaller than 75% of the EU25 average (see the fifth data column of Table 2). Suppose 1999 would have been the decisive year for the determination of Objective 1 eligibility for all regions in the EU25 countries. In this case, the Baltic countries (Estonia, Latvia, and Lithuania) as well as Poland would have been eligible in total.[10] Instead, none of the NUTS2 regions in a country would be eligible for Objective 1 transfers if the minimum GDP per capita in a region were higher than 75% of the EU25 average. This is the case for Luxembourg, Cyprus, and Malta (all of them cases of small countries consisting of only one NUTS2 region) as well as for Belgium, Denmark, Finland, France, Ireland, the Netherlands, and Sweden. However, the actual eligibility criterion applied for the 2000-06 programming period was somewhat different from that: the NUTS2 average GDP per capita over the years 1994-96 relative to the Community average was used for the EU15 countries while the average over the years 1997-99 was applied for the accession countries of 2004.

Table 3 about here

Since a region's initial GDP per capita is the only official criterion for Objective 1 status, Table 3 compares treated and non-treated regions with respect to the difference in their GDP per capita. The prime target of Objective 1 transfers is the reduction of this gap. Not surprisingly, the average difference in per-capita GDP between Objective 1 and non-Objective 1 regions in column 3 increases as further countries join the EU over the course of the three programming periods. In 1988, for the EU12, the average NUTS2 recipient region had a per-capita GDP that was 63% of the average non-recipient region. In 1999, for the EU25, the average recipient region had a per-capita GDP that was 53% of the average non-recipient region.

[9]Cyprus, Malta, and 8 Central and Eastern European countries: Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Slovenia, Slovak Republic.

[10]Of course, actual Objective 1 transfer eligibility of the Baltic countries as well as Poland became only relevant after their EU membership in 2004.

Given the ex ante differences between Objective 1 and non-Objective 1 regions, an unconditional comparison of their economic performance seems like comparing apples to oranges. The main problem is that real per-capita GDP determines not only the probability of Objective 1 *treatment* but – according to the convergence hypothesis – also the growth of real per-capita income (the *outcome*). Hence, the challenge is to disentangle the impact of initial levels of real per capita income on growth per se from the discontinuity related to and associated with Objective 1 at a level of per-capita income which is less than 75% of the EU average.

Table 4 and Figure 2 about here

Table 4 shows that some regions got treated even though they were too rich to be formally eligible and others were not treated even though they were poor enough to be eligible. Across the three programming periods 1989-93, 1994-99, and 2000-06, the number of observations which comply with the 75%-rule is 628 (out of 674) for NUTS2 regions and 3,142 (out of 3,300) for NUTS3 regions. Only about 7% of all regions are thus exceptions from the rule.

Still, this calls for a *fuzzy* regression-discontinuity design. For it to be a *sharp* regression-discontinuity design (see Imbens and Lemieux, 2008, as well as Angrist and Pischke, 2009 and Lee and Lemieux, 2009, for a general discussion of RDD), there should be no exceptions from the 75%-rule.

Figure 2 illustrates graphically how the probability of Objective 1 treatment relates to region-specific per-capita GDP at PPP prior to a programming period. We follow Lee (2008) and Lee and Lemieux (2009) and display average treatment rates in equally sized bins of width of two percentage points to the left and the right of the threshold.

The main feature of a fuzzy RDD is that the extent of the discontinuity in treatment probability is smaller than unity. As we approach the 75%-threshold from below, some regions that would be formally eligible do not obtain Objective 1 status. Hence, the probability of Objective 1 status is smaller than unity. For instance, the UK did not deliver GDP data at the NUTS2-level at the time Objective 1 status was determined in the programming period 1989-93. Only ex post, when the data became available, it turned out that some British NUTS2 regions should have been eligible for Objective 1 funds. As we approach the 75%-threshold from above, the probability of Objective 1 status exceeds zero, witnessing cases where governments negotiated exceptions from the 75% rule for regions which were too rich to be formally eligible (see footnote 3 for further details).

Figure 3 about here

To illustrate the effect of the discontinuity in Objective 1 treatment on economic outcomes, we plot local polynomial functions of per-capita GDP at PPP prior to each programming period (the forcing variable) against average annual growth of per-capita GDP at PPP during that period (an outcome) based on local averages of the forcing variable.[11] Identification of a causal effect of Objective 1 treatment on growth by means of RDD requires that there is a discontinuity at the threshold in both Figures 2 and 3. The results in the figures are promising in that regard, since the discontinuity in Figure 2 is obvious.[12]

However, Figures 2 and 3 suggest that the design is fuzzy. To see this, in Figure 3 we use circles for those observations for which the 75% rule is correctly applied. Crosses indicate observations which did not receive Objective 1 funds despite being formally eligible (to the left of the threshold) or received Objective 1 funds despite not being formally eligible (to the right of the threshold). Notice that the majority of crosses are generally positioned *below* the local polynomial to the *left* of the threshold but *above* the local polynomial to the *right* of the threshold. Hence, the treatment effect is underestimated by the discontinuity at the threshold in Figure 3. A consistent estimate of the discontinuity can, however, be obtained by instrumental variable estimation when using the (Objective 1) treatment eligibility rule as an instrument (see Wooldridge, 2002, and Angrist and Pischke, 2009). Accordingly, we proceed in the next section with identifying the treatment effect by means of instrumental variables regressions.

Before we proceed to the regression analysis, Table 5 displays descriptive statistics of the variables entering in our regressions.

Table 5 about here

In particular, this table provides information on four moments of the distribution of all variables in use, namely the mean, the standard deviation, the minimum, and the maximum. The outcome variables are GDP per capita growth in three programming periods at the NUTS2 level, GDP per capita growth in three programming periods at the NUTS3 level, employment growth in three programming periods at the NUTS2 level, employment growth in three programming periods at the NUTS3

[11] The number of NUTS2 observations is 674, so that estimating local polynomial functions is demanding. However, using, e.g., a parametric fifth-order polynomial function, Figure 3 leads to polynomial functions to the right and the left of the treatment threshold which are virtually undistinguishable from nonparametric local polynomials. The corresponding figure based on nonparametric local polynomials is available from the authors upon request.

[12] Also, the 95% confidence intervals of the local polynomial functions to the right and the left of the 75% per-capita income threshold in Figure 3 are non-overlapping. We suppress these confidence intervals for the sake of better readability of the figure.

level.[13] The table also displays descriptives for the Objective 1 treatment indicator in three programming periods at the NUTS2 level and at the NUTS3 level and for the average GDP per capita in threshold years (i.e., prior to the respective three programming periods).

Finally, the table shows descriptives for covariates: the employment share, the agricultural share (in total employment), the service share (in total employment), the population growth rate, the population density (in 1,000 inhabitants per square km), and the Shapley-Shubik index of voting power in the EU Council. We use covariates to probe the credibility of the RD design in specification tests and robustness checks in Section 5.

4 Regression analysis

We seek to estimate the causal effect of Objective 1 status on regional economic performance by means of regression analysis. Below, we will employ regression models for fuzzy RDD. Let us briefly introduce such models in formal accounts before we discuss the associated results with the data at hand.

4.1 The regression-discontinuity design (RDD)

Think of a NUTS2 region A with a GDP per capita of 74.99% and a NUTS2 region B with a GDP per capita of 75.01%, one formally eligible for Objective 1 transfers, one not. These two regions are certainly more comparable than regions far away from the threshold. In our context, the reason is simply that – on average – regions whose per-capita income differs starkly at a point in time grow quite differently (according to the convergence hypothesis) while regions with a similar per-capita income level should also display similar growth rates thereof at that point. The crucial question is whether the discontinuity at the threshold associated with Objective 1 status is discernible from a polynomial function of reasonable order about the per-capita income level.

Figure 2 illustrates that, with partial non-compliance, the 75%-rule gives rise to a fuzzy RDD that requires instrumental variables estimation. Let us use the following notation to outline the model. $Growth_{it}$ denotes average annual growth of region i's real per-capita income in PPP terms or of employment during programming period t (i.e., 1989-93; 1994-99; 2000-06). $Treat_{it}$ is a binary indicator variable for Objective 1 treatment which is unity in case of treatment of region i in programming

[13] Regression results are robust when excluding East German regions in 1989-93 which are behind some of the large minima and maxima for GDP and employment growth.

period t and zero else. $Rule_{it}$ is a binary indicator variable for Objective 1 eligibility which is unity in case of eligibility of region i in period t according to the 75% rule and zero else. With a fuzzy design, $Treat_{it}$ may be unity when $Rule_{it}$ is zero, and vice versa. Suppose the continuous relationship between $Growth_{it}$ and the forcing variable $Force_{it}$ (reflecting per-capita income in PPP prior to programming period t)[14] can be captured by a P^{th}-order parametric polynomial function $f(Force_{it})$, whose parameters may be restricted to be the same or allowed to differ to the right and the left of the threshold.[15]

Ultimately, we want to estimate the regression discontinuity parameter ρ on $Treat_{it}$ by means of a regression of the following form (see Angrist and Pischke, 2009):

$$Growth_{it} = \theta_t + \rho Treat_{it} + f(Force_{it}) + \lambda_i + \mu_{it}, \tag{1}$$

where θ_t is a time-specific constant, λ_i is a region-specific effect that may be random or fixed,[16] and μ_{it} is a possibly heteroskedastic disturbance term. With a fuzzy design, ordinary least squares estimation on (1) results in a biased estimate of the average treatment effect as captured by ρ (see Cook, 2008; Imbens and Lemieux, 2008; Lee and Lemieux, 2009). However, an unbiased estimate can be obtained by two-stages least squares, where $Treat_{it}$ in (1) may be instrumented by a first stage regression of the form

$$\begin{aligned} Treat_{it} &= \alpha_t + \beta Rule_{it} + f(Force_{it}) + \kappa_i + \epsilon_{it} && (2) \\ &or \\ P(Treat_{it} = 1) &= f(\delta_t + \zeta Rule_{it} + f(Force_{it}) + \xi_i + \nu_{it}), && (3) \end{aligned}$$

with α_t, β, δ_t, ζ, κ_i, and ξ_i denoting unknown parameters, and ϵ_{it} and ν_{it} denoting disturbances, respectively.[17] Notice that irrespective of whether we use $Rule_{it}$ in a linear first stage or the prediction of $P(Treat_{it} = 1)$ with a nonlinear first-stage as an identifying instrument for $Treat_{it}$ in the second stage, the fuzzy-design

[14] See the discussion above for details on the years which the European Commission considered to determine Objective 1 treatment status based on real per-capita income.

[15] For this, $Force_{it}$ has to be normalized properly so that the parameter of $Treat_{it}$ captures the regression discontinuity (see Angrist and Pischke, 2009, p. 255). Then, depending on the parametric assumption, either P or $2P$ parameters have to be estimated. In our case, we will estimate models based on 3^{rd}-order, 4^{th}-order, and 5^{th}-order parametric polynomial functions.

[16] With fixed λ_i, we may include region-specific indicator variables or, where more convenient, averages of all right-hand-side variables across the programming periods t as in Mundlak (1978).

[17] To avoid the incidental parameters problem with a nonlinear first-stage model as in (3), ξ_i can be parameterized by including means of all covariates in (3) across all periods (analogous to Mundlak, 1978) or by including period-specific means (analogous to Chamberlain, 1984; Wooldridge, 2002).

instrumental-variable model is just identified. While some distributional assumption has to be made for the nonlinear probability model, this is not the case for the linear probability model. However, with a linear probability model, ϵ_{it} will be generally heteroskedastic. In what follows, we will generally use nonlinear probability models in the first stage, but the results are very similar to those obtained with a linear probability model in the first stage. In general, we correct the estimated variance-covariance matrix for clustering at the level of regions and for heteroskedasticity of arbitrary form.

Tables 6 and 7

Tables 6 and 7 summarize our findings for six different models each. The models in columns (1), (3), and (5) are estimated by pooled OLS and the ones in columns (2), (4), and (6) include fixed effects at the NUTS2 level. For both pooled OLS and fixed effects estimates, there are three models in each table: in columns (1) and (2) we use a 3^{rd}-order polynomial for $f(Force_{it})$, in columns (3) and (4) we use a 4^{th}-order polynomial, and in columns (5) and (6) we use a 5^{th}-order polynomial, respectively. While the parameters of the polynomial function are assumed to be identical on both sides of the threshold in Table 6, the parameters are allowed to differ to the right of the threshold from the left in Table 7. In either table we use a non-linear first-stage model as in (3).

The results display the following pattern. First of all, there is no evidence of significant effects on average employment growth induced by Objective 1 treatment in any of the specifications in Tables 6 and 7. In contrast, there is robust evidence of a positive impact of Objective 1 treatment on GDP/capita growth. However, the point estimates tend to be larger in Table 6 than in Table 7. Given the flexibility of the estimates based on separate (asymmetric) polynomial functions to the right and the left of the eligibility threshold, we prefer the estimates in Table 7 to the ones in Table 6, even though statistical tests of symmetric polynomials vs asymmetric polynomials do not reject the null hypothesis of a symmetric polynomial function about the threshold at 10%. The treatment effect estimates in columns (1), (3), and (5) of Table 7 are significantly different from zero at least at 15% statistical significance across the board. The ones in columns (2), (4), and (6) are significantly different from zero at least at the 10%-level across the board.[18] In terms of order of the polynomials, it seems preferable to use at least fourth-order polynomials rather than a 3^{rd}-order polynomial function to model the continuous relationship in $f(Force_{it})$ of (1): 5^{th}-order terms are jointly significant in columns (5) and (6) and so are 4^{th}-order terms in columns (3) and (4) of Table 7.

[18] Notice also that somewhat more efficient estimates can be obtained when using NUTS3 regional data rather than NUTS2 data. See the next section for a discussion of these estimates.

Overall, we identify a positive effect of Objective 1 treatment on per-capita GDP growth that is significantly different from zero in both Tables 6 and 7, but there is no such effect on employment growth.

We consider column (6) of Table 7 to be our reference specification. The reason is that, with the data at hand, the region-specific effects are marginally jointly statistically significant. Moreover, 5^{th}-order polynomials have a somewhat better fit than polynomials of a lower degree and 5^{th}-order terms are jointly significant. Finally, asymmetric polynomial functions to the right and the left of the threshold are more flexible than symmetric ones, even though there is no strong statistical indication against pooling the parameters of $f(Force_{it})$ to the left and the right of the threshold. However, point estimates for the treatment effect with asymmetric polynomial terms are generally more conservative, so that they can be considered as lower bounds in our analysis.

5 Specification tests, sensitivity checks, and evaluation.

5.1 Sensitivity checks and extensions

In a next step, we check the sensitivity of the results in a number of regards and summarize the results of interest in Table 8. For the sake of brevity, let us focus on sensitivity checks for the benchmark model in column (6) of Table 7 in what follows. Table 8 contains five blocs of results in a vertical dimension, numbered (I)-(V), and two blocs in a horizontal dimension. The bloc on the left refers to Objective 1 effects on GDP per capita growth (as in the upper part of Table 7) and the one on the right to employment growth (as in the lower part of Table 7). Vertically, blocs (I)-(III) represent sensitivity checks while blocs (IV)-(V) represent extensions. Let us use the same enumeration below as in Table 8 to discuss the corresponding findings.

Table 8 about here

(I) Using NUTS3 rather than NUTS2 outcome and treatment Some of the fuzzyness of the design is created since the European Commission assigns Objective 1 transfers to some of the NUTS3 regions rather than NUTS2 regions. This justifies using NUTS3 data on outcome ($Growth_{it}$) and treatment ($Treat_{it}$) besides NUTS2 data. However, the assignment rule ($Rule_{it}$) and the forcing variable ($Force_{it}$) refer to the NUTS2 level, since the rule principally applies at the NUTS2 level. Using such an approach at the top of Table 8 leads to a point estimate at the NUTS3 level in a regression as in column (6) of Table 7 which is somewhat higher than the one in Table 7. However, there is no indication of an impact on employment growth, similar to Table 7.[19]

The assignment of funds might be partly correlated with NUTS3 population size, population density, employment share in total population, service share in total employment, agricultural share in total employment, and with voting power at the country level in the EU level (captured by a Shapley-Shubik index which is calculated at the country level).[20] Controlling for these variables at the NUTS3 level reduces the point estimate for Objective 1 treatment in the model of GDP per capita capita growth from 0.017 to 0.012 but does not affect the significance of the estimate. Again, there is no effect on the employment growth in the corresponding regressions.

(II) Using only data within certain windows around the treatment threshold In the second bloc of Table 8, we report estimates for per-capita GDP growth and employment growth for sub-samples of the data within certain windows around the treatment threshold. We use symmetric windows for the forcing variable of 60%-90%, 65%-85%, and 70%-80% of EU average per-capita GDP prior to a programming period, respectively. This idea is described by Lee and Lemieux (2009) and serves to contrast the polynomial estimation approach with a kind of local linear regression approach where window width around the cutoff point is varied. Of course, this strategy reduces the number of observations dramatically, namely from 674 in Table 7 to 248, 168, and 76, respectively. Yet, with data in smaller windows around the treatment threshold, there is less chance that the polynomial function $f(Force_{it})$ is misspecified. Therefore, we can even reduce the degree of the polynomial functions within the windows. In bloc (II) of Table 8, we estimate 3^{rd}-order and 2^{nd} order polynomials, alternatively. It turns out that the point estimates are in the range of those of columns (5) and (6) in Table 7 for growth of GDP/capita and they are not significantly different from zero for employment growth as before.

(III) Controlling for spillover effects One concern with the estimates in Tables 6 and 7 is that Objective 1 transfers may be used to finance public infrastructure,

[19]Note that we always correct the estimated variance-covariance for clustering at the NUTS3 level whenever cross-sectional units correspond to NUTS3 rather than NUTS2 regions.

[20]It might cast doubt on the regression discontinuity design, if not only outcome but also these covariates displayed a discontinuity at the threshold. In Figure 4 contained in the next subsection, we will illustrate that this is not the case. However, even in the absence of jumps in covariates at the 75% threshold, a natural robustness check is to include the covariates in the regressions (see Lee and Lemieux, 2009).

generating not only local effects on the treated regions but also spillovers to neighboring regions. The latter would violate the so-called *stable unit treatment value assumption* and, with positive spillover effects, eventually lead to downward-biased estimates of the average Objective 1 treatment effect, unless spillovers are captured by the polynomial function of NUTS2 per-capita income. The reason is that positive spillovers reduce the difference between growth rates of the treated and the untreated regions.

Provided that the aforementioned spillovers are of medium reach (e.g., they do not exceed a distance of 150-200 kilometers), such a bias can be avoided by either excluding untreated units within a radius of 150 or 200 kilometers or, even better, by including an indicator variable which is unity if neighboring regions within a radius of 150 or 200 kilometers received treatment.[21] The corresponding estimates, especially the ones assuming a maximum radius of spillovers of 200 kilometers, would then be free of a downward bias from spillovers.

Bloc (III) of Table 8 provides four experiments to tackle the possible problem of spillovers which underly the same parametrization and assumptions as the models for GDP per capita growth and employment growth in column (6) of Table 7. The first two of the models rely on a spatial exclusion approach, where control regions are excluded if they have a treated region within a radius of 150 and 200 kilometers, respectively. Obviously, the number of observations declines with a larger radius applied around Objective 1 treated regions. By excluding control units with a treated unit within a radius of 150 and 200 kilometers the number of NUTS2 observations drops from 674 in Table 7 to 581 and 535, respectively. The last two rows in bloc (III) directly control for spillovers from treated regions within a radius of 150 and 200 kilometers, respectively, by using an indicator variable which is equal to one if other NUTS2 regions got treated within a radius of 150km or 200km, respectively. Then, the number of observations is the same as in Table 7.

A comparison of the results between column (6) in Table 7 and bloc (III) of Table 8 suggests that controlling for spillovers does not affect the point estimates to a large extent. With spatial exclusion and growth of GDP per capita as the outcome, the point estimates of Objective 1 treatment are virtually indistinguishable from the previous ones. With the control approach at the bottom of bloc (III), the point estimates are somewhat smaller than in Table 7. However, note that the total effect of treatment now consists of direct effects and spillover effects, where the latter

[21]We have conducted a Monte Carlo analysis suggesting that even with reasonably small samples of observations either approach leads to unbiased estimates of the average treatment effect in RDD. Results are available from the authors upon request. Admittedly, this ignores Objective 1-induced (second or higher order) spillover effects from untreated regions to other untreated regions, but these should be negligible with spillovers of reasonable magnitude.

amounts to 0.005 (significant at 1%) with a radius of 150 kilometers and to 0.007 (significant at 1%) with a radius of 200 kilometers. Hence, these point estimates have to be added to the direct effects to account for the total impact of the treated as compared to untreated outside a radius of 150 or 200 kilometers from treated regions.

For employment growth, the point estimates of the spatial exclusion mechanism are similar to the one in Table 7. However, the spatial control regressions obtain point estimates which are about twice the ones in Table 7, and these point estimates are significantly different at conventional levels. Moreover, the spillover parameters are 0.003 (significant at 15%) wit 150 kilometers and 0.004 (significant at 1%). Hence, the spatial models indicate that naïve regressions which ignore spillovers may conceal or fail to unveil some effects of Objective 1 treatment on employment growth while this is less of an issue with growth of GDP per capita as the outcome.

When taking into account moderate cross-regional spillovers as in the last experiment of bloc (III) in Table 8, the total impact of Objective 1 treatment on average annual growth of GDP per capita is estimated at 0.013 for treated regions *without* other treated units within a radius of 200 kilometers and at $0.013 + 0.007 = 0.020$ for treated regions *with* other treated units within a radius of 200 kilometers. Notice that the fraction of NUTS2 regions with spillovers from other regions within a radius of 200 kilometers is 0.482. Hence, about 48% of the NUTS2 regions receive spillovers and about 52% do not. Roughly, the average Objective 1 treatment effect on average annual growth of GDP per capita is then $0.482\cdot(\cdot 0.013+0.832\cdot 0.007)+0.518\cdot 0.007 = 0.013$, which is similar to the estimates based on spatial exclusion at the top of bloc (III) and also the one in column (6) of Table 7.

We conclude that cross-regional spillovers are relatively modest in absolute terms for growth of both GDP per capita and employment. However, they are relatively more important for employment growth. One reason for the latter finding may be that workers are keen on taking jobs in treated regions but less so on changing their residence.

(IV) Estimating effects by programming period Notice that the forcing variable is defined in a unique way across all programming periods and the treatment rule by period refers to regional GDP per capita relative to the relevant period-specific EU average throughout, leaving the cut-off point unchanged in relative terms (the 75% rule). However, it may be interesting to see whether the impact of Objective 1 treatment on NUTS2 regional growth of either GDP per capita or employment is relatively homogeneous across programming periods or not. Bloc (IV) in Table 8 summarizes findings from RDD regressions for each programming period separately.

Since these regressions do not identify significant effects on employment growth, similar to our findings from Table 7, we may focus on the role of Objective 1 treatment for growth of GDP per capita. Notice that the number of regions covered changes across periods so that the parameter estimates are not directly comparable. For all programming periods, the estimated treatment effect is significantly different from zero at least at 15%. The point estimate for the period 1994-99 is the smallest one and carries the largest standard error in relative terms. The parameter estimate in the period 1989-93 is largest and significantly different from zero at 5%. However, a 90% confidence interval around any of the coefficients includes the point estimate reported in column (6) of Table 7.[22]

(V) Assessing the accumulation of Objective 1 effects on growth over time
Another way of considering time-specific treatment effects is to consider a possibly dynamic adjustment behind the average effect in Table 7. For this, we may consider Objective 1 average annual treatment effects which are obtained up to one, two, three, four, five, and even six years after the beginning of a programming period.[23] However, for this exercise it is particularly important to note that the programming periods are of unequal length. The first programming period may only enter the estimation of dynamic effects up to four years after the beginning of a budgeting period. The third programming is the only one which can inform us about the effects which are accumulated up to six years after the beginning of a budgeting period. Notice that pooling the data for particular time spans when looking at adjustment dynamics may be more harmful than considering average growth effects until the end of a budgeting period of arbitrary size, because regions have to spend allotted funds more quickly in shorter than in longer programming periods.

The results are reported in bloc (V) of Table 8 and may be summarized as follows. First, on average, it takes at least four years until significant effects of Objective 1 treatment on average annual growth of GDP per capita may be detected. Notice that the first programming period lasted only for 5 years while slightly more than half of the third programming period (7 years) had passed. The treatment effect on GDP-per-capita growth increases after the fourth year and approaches the value we reported for the last programming period in bloc (IV) at the bottom of bloc (V) for up to six years after the start of a programming period.[24] In general, the

[22]Notice that the largest period-specific coefficient also obtains the smallest weight in the pooled models of Table 7, since the number of observations is smallest. A simple frequency-weighted average of the period-specific coefficients in Table 8 would obtain a point estimate of 0.025, which is somewhat higher than its counterpart from a pooled fixed effects model as in Table 7.

[23]For reasons of comparability, we report average annual effects. However, these are just geometric means over the respective number of years, so that it is straightforward to retrieve total effects up to a specific year instead of average annual growth effects.

[24]As said before, only data for the last programming period enter that computation.

results do not point to employment growth effects of Objective 1 treatment which are significantly different for any of the considered time spans.

5.2 Specification tests

To assess the credibility of the RDD strategy, we inspect graphs of covariates used in bloc (I) of Table 8 at the 75% threshold. If any of these graphs displayed a jump at the treatment threshold this might cast doubt on the RD design (see Imbens and Lemieux, 2008). Figure 4 shows averages of various covariates in equally sized bins of 2% which are plotted against the per capita GDP that applied in the years relevant for the decision about Objective 1 status. Again, we estimate 5^{th}-order polynomial functions to the left and the right of the 75% threshold. There is no indication of a jump at the 75% threshold in any of the plots in Figure 4.[25]

Figures 4 and 5 about here

Furthermore, we inspect an RDD plot on the size of grants to assess whether there is a significant jump in the size of Objective 1 grants around the treatment threshold in Figure 5. If there were only a small change in the size of Objective 1 grants around the threshold but a relatively sizable treatment effect estimated from our RDD in Section 4 this would seem implausible, since a "small" treatment dose would unlikely cause a large treatment effect. However, Figure 5 suggests that Objective 1 funds as a fraction of initial GDP do jump significantly at the threshold from about zero to more than three percent of GDP.

We consider both specification tests as supportive of our RD design.

5.3 Assessing the net benefits of Objective 1 treatment

With the estimates at hand and based on a back-of-the-envelope calculation, we may infer whether the use of Objective 1 transfers is justified on average or not, when requiring positive net benefits within a programming period. In column (6) of Table 7, the estimate of the Objective 1 on GDP-per-capita growth is 0.016. Accordingly,

[25]Note that even if there had been a jump at the 75% threshold, this would not have necessarily invalidated our design (see Imbens and Lemieux, 2008, p. 632). To see this, assume that there had been a jump at the 75% threshold for the voting power in the EU council, measured by the Shapley-Shubik index. This would have indicated that certain countries are more successful in bending the rules, giving rise to the fuzzyness we observe. However, only if the voting power also directly affects GDP growth rates would it have led to biased estimates. Of course, the fact that we do *not* observe jumps at the 75% threshold in any of the covariates is even more comforting and lends credibility to our design.

Objective 1 treatment raised average growth of real GDP per capita by about 1.6 percentage points in recipient regions. The level of GDP per capita and GDP (at PPP) in the average treated NUTS2 region and year amounted to 11,074 Euro and 16,000 million Euros, respectively.[26] The average Objective 1 NUTS2 region's population changed only slightly over the average period with an annual growth rate of 0.1%. Hence, Objective 1 treatment caused absolute GDP to change by about the same rate as per-capita GDP, namely by 1.6% or 256 million Euros (at PPP) per annum in the average treated region and programming period. Aggregating this effect up for all treated regions in the average programming period results in a treatment effect of 18.45 billion Euros (at PPP) per year within the EU as a whole.[27] The total cost of the Objective 1 programme was 15.33 billion Euro (at PPP) per annum in the average programming period (see Table 1). Then, we may conclude that the Objective 1 programme induces a net effect of 3.12 billion Euros (at PPP) per year or 20% of the expenses per year in the EU as a whole. In other words, every Euro spent on Objective 1 transfers leads to 1.20 EUR of additional GDP.[28]

Note that this back-of-the envelope calculation is based on the point estimate of the benchmark specification in column (6) of Table 7. Taking into account the confidence interval around that point estimate, we cannot exclude a multiplier of 1 instead of 1.2. However, as indicated before in Section 4, it would be justified from a statistical point of view to constrain the polynomial functions to be symmetric

[26]Taking GDP and GDP per capita prior to each single programming period, i.e., in 1988 for the EU12 in the first period and 1989 for the German New Länder, 1993 for the EU12 and 1994 for Austria, Finland, and Sweden in the second period, 1999 for the EU15 and 2003 for the new accession countries in the third programming period considered here.

[27]There were 58 treated NUTS2 regions in the first period of which the 11 New Länder regions received funds only for 4 years. In the second period, there were 64 treated NUTS2 regions of which the Austrian NUTS2 region Burgenland received funds only in 5 out of 6 years, and in the third period there were 129 treated NUTS2 regions of which the 67 Objective 1 regions in the new accession countries received funds only from 2004 onwards, that is for 3 rather than 7 years. This makes a total of 1,297 region-year observations of Objective 1 treatment or, on average, 72.06 regions per annum receiving treatment over the three periods.

[28]There are three important assumptions behind this calculation, two about the consequences and another one about the costs. Regarding consequences, we assume that (i) all effects of Objective 1 treatment materialize until the end of a programming period, and (ii) that the treatment effect is fairly homogeneous across regions (i.e., the discontinuity at the threshold reflects the treatment effect for the average treated region). Relaxing the latter assumption would be beyond the scope of RDD analysis. Regarding costs, we assume that the associated collection of taxes does not distort economic activity in net paying regions. Moreover, we abstract from administrative costs associated with the collection of these taxes. Hence, we assume that one Euro of Objective 1 transfers is identical to one Euro of costs. However, for a violation of the assumption of non-distortionary taxation, one would have to blame the taxing authorities at the national level rather than the European Commission.

about the treatment threshold as in column (6) of Table 6 which would lead to an even larger multiplier effect. A conservative view is thus to interpret the back-of-the-envelope calculation as saying that the Objective 1 funds might generate a mild multiplier effect, but we cannot reject multipliers of unity.

6 Concluding remarks

This paper considers the estimation of causal effects of the European Union's (EU) Objective 1 transfers on economic growth. Objective 1 funds aim at facilitating convergence and cohesion within the EU and constitute the major part of the EU's *Structural Funds Programme*. They target fairly large, sub-national regional aggregates – referred to as NUTS2 regions – to foster growth in regions, whose per-capita GDP in purchasing power parity is lower than 75% of the EU's average per-capita income.

The 75%-rule gives rise to a regression-discontinuity design that exploits the jump in the probability of Objective 1 recipience at the threshold. In the vast majority of cases (93% of the observations at NUTS2 level), the 75%-rule is strictly applied. Only 7% of our observations do not comply with the assignment mechanism. These are regions which either obtained Objective 1 funds although they were not eligible according to the rule or they did not receive funds although they were eligible. This leads to a fuzzy regression-discontinuity design for the impact of Objective 1 treatment on growth.

Our results can be summarized as follows. On average, Objective 1 status raises real GDP per capita growth by roughly 1.6% within the same programming period. Second, different from the positive effects on per-capita GDP, we do not find significant employment effects during the period in which transfers are allocated, unless we allow for spillover effects from treated regions within a radius of up to 200 kilometers. There may be various reasons an positive GDP growth effect and the absence of an employment growth effect. One reason could be that Objective 1 transfers mainly stimulate the volume and change the structure of investment. Another reason could be that job creation takes longer than the duration of a programming period of five to seven years.

We perform several robustness checks. First, we estimate treatment effects at the level of NUTS3 rather than NUTS2 regions. Second, we deal with possible spillovers of Objective 1 funds on neighboring regions by estimating separate regressions in which we exclude control regions adjacent to treated regions. Third, we estimate the treatment effect within windows of the forcing variable of Objective 1 treatment – namely per-capita income at PPP in relevant years prior to a programming period.

Fourth, we provide estimates separately for three sub-periods. Fifth, we estimate the dynamics behind the impact on average annual growth along the years from the start of a programming period.

Our results are qualitatively robust to these checks. They suggest that the treatment effect varies across programming periods, but with overlapping confidence intervals of reasonable size. Objective 1 treatment status does not cause immediate effects but takes, in the average programming period and region, at least four years to display growth effects on GDP per capita.

A simple back-of-the envelope calculation of the net benefits of Objective 1 transfers suggests the following. According to our benchmark estimates, every Euro spent on Objective 1 transfers leads to 1.20 Euros of additional GDP. The latter is probably associated with a stimulus on the volume and structure investment (e.g., infrastructure) and, eventually, productivity gains but much less so with the creation of new jobs within the same programming period. From this, we may conclude that, on average, Objective 1 transfers under the EU's *Structural Funds Programme* might well be effective and – in net terms – not wasteful.

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7 Tables and Figures

Table 1: Objective 1 regions

	1989-1993	1994-1999	2000-2006
	(1)	(2)	(3)
NUTS2			
Total Number of NUTS2 Regions	193	215	285
Number of Obj.1 NUTS2 Regions	58	64	129
NUTS3			
Total Number of NUTS3 Regions	1015	1091	1213
Number of Obj.1 NUTS3 Regions	286	309	417
Overall yearly funds (Mio. Euro)	8764	15662	15306
Overall yearly funds (Mio. Euro PPP)	10279	17479	17086
Yearly funds as fraction of Obj. 1 NUTS2 region GDP	.014	.018	.011
Yearly funds per inhabitant of Obj. 1 NUTS2 region (Euro PPP)	125	193	229

Notes: Data on EU Structural Funds stem from European Commission (1997 pp. 154-155 and 2007 p. 202). To obtain average yearly funds we divide period-specific figures by the number of years the respective programming period lasted. We calculate the funds in PPP terms by weighting the funds each single country received in the respective programming period with the country's Purchasing Power Parity Index of the programming period's initial year. Funds per GDP and funds per inhabitant are calculated as the average yearly funds divided by regional GDP and regional population, respectively, prior to the programming period. This is 1988 and 1989 for the EU12 and the German New Länder, respectively, in the first period, 1993 for the EU12 regions in the second period but 1994 for the countries joining in 1995 (Austria, Finland, and Sweden), and 1999 for the EU15 in the third 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 5 years and 4 years for the EU12 and the German New Länder, respectively, in the first period, 6 years and 5 years for the EU12 and the new members of 1995, respectively, in the second period, and 7 years for the EU15 but 3 years for the new accession countries of 2004. 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 for the years 1989 and 1990 using information from the GDR's statistical yearbook.

Table 2: Disparities in the EU25 1999 (GDP per capita PPP)

	Country Avg. (Euro PPP)	Country Max (Euro PPP)	Country Min (Euro PPP)	Country Avg. rel. to EU25	Country Max rel. to EU25	Country Min rel. to EU25
Austria	18855.38	29546.84	13446.46	1.02	1.59	.72
Belgium	18466.26	43347.16	14331.10	.99	2.34	.77
Cyprus	14861.88	14861.88	14861.88	.80	.80	.80
Czech Republic	11411.80	23708.24	9554.07	.61	1.28	.51
Germany	19929.09	35739.29	12738.76	1.07	1.93	.69
Denmark	22634.88	27954.49	17869.64	1.22	1.51	.96
Estonia	6252.50	10644.65	4636.73	.34	.57	.25
Spain	16005.10	22823.61	11146.41	.86	1.23	.60
Finland	20302.39	28662.20	15392.66	1.09	1.54	.83
France	19790.04	32908.45	16100.37	1.07	1.77	.87
Greece	12530.61	16631.15	9377.14	.68	.90	.51
Hungary	8598.66	14861.88	6192.45	.46	.80	.33
Ireland	21651.46	24769.80	16454.23	1.17	1.33	.89
Italy	21184.88	29900.69	12915.68	1.14	1.61	.70
Lithuania	6243.72	9153.68	4171.41	.34	.49	.22
Luxembourg	40693.25	40693.25	40693.25	2.19	2.19	2.19
Latvia	5296.85	10829.71	3191.77	.29	.58	.17
Malta	14508.03	14508.03	14508.03	.78	.78	.78
Netherland	22107.05	29016.05	16808.08	1.19	1.56	.91
Poland	8382.42	13092.61	6015.52	.45	.71	.32
Portugal	13250.58	21408.19	12207.97	.71	1.15	.66
Sweden	19942.22	30431.47	18754.28	1.07	1.64	1.01
Slovenia	12438.66	19182.09	9761.78	.67	1.03	.53
Slovak Republic	8824.24	18931.21	6546.31	.48	1.02	.35
United Kingdom	19392.81	49362.68	12384.90	1.04	2.66	.67

Notes: The table shows average, maximum and minimum GDP per capita (at PPP terms) within a country for NUTS2 regions. We miss information on the four French overseas-départements and the two autonomous Portuguese regions Madeira and Azores.

Table 3: Objective 1 recipient vs. non-recipient regions

	Mean recipient	Mean non-recipient	Difference col.(1)-col.(2)	Std. Err. of col.(3)
	(1)	(2)	(3)	(4)
EU12				
GDP per capita 1988	8586.20	13634.19	-5047.99	478.23
No. of observations	52	134		
EU15				
GDP per capita 1993	10795.99	16298.13	-5502.14	536.56
No. of observations	58	151		
EU25				
GDP per capita 1999	11157.73	21251.68	-10093.94	556.27
No. of observations	123	156		

Notes: The table shows differences in GDP per capita (PPP) of recipient and non-recipient regions at the NUTS2 level. 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 statistical yearbook.

Table 4: Eligibility and actual treatment under Objective 1 according to 75% GDP per capita threshold

	Recipients	Non-recipients	Recipients	Non-recipients
	NUTS2	NUTS2	NUTS3	NUTS3
1989-93 EU12				
Eligible	43	4	246	98
Non Eligible	9	130	34	631
1994-99 EU15				
Eligible	44	3	260	108
Non Eligible	14	148	43	674
2000-06 EU25				
Eligible	111	4	345	95
Non Eligible	12	152	66	701

Notes: Eligible regions are characterized by a GDP per capita of less than 75% of EU average in the qualifying years of each programming period (3-year average over the years preceding the start of a new programming period). Recipient regions are those that did effectively receive Objective 1 status. 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 and NUTS3 regions we calculated GDP per capita growth for the years 1989 and 1990 using information from the GDR's statistical yearbook.

Table 5: Descriptive Statistics

	Mean	Std. Dev.	Min	Max
	(1)	(2)	(3)	(4)
GDP per capita growth (NUTS2)	.042	.018	-.008	.131
GDP per capita growth (NUTS3)	.041	.022	-.039	.251
Employment growth (NUTS2)	.005	.014	-.062	.079
Employment growth (NUTS3)	.005	.022	-.162	.273
Objective 1 (NUTS2)	.306	.461	0	1
Objective 1 (NUTS3)	.305	.46	0	1
Avg. GDP per capita threshold years	12927.27	4562.467	3343.816	37835.19
Employment share	.427	.119	.017	1.634
Industry share	.304	.103	0	.764
Service share	.613	.122	.031	.997
Population	350.670	435.757	14.282	5157.201
Population density	.492	1.065	.002	20.381
Shapley-Shubik index	.103	.04	0	.134

Notes: 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 and NUTS3 regions we calculated GDP per capita growth for the years 1989 and 1990 using information from the GDR's statistical yearbook.

Table 6: RDD NUTS2 - Objective 1 and GDP per capita/Employment growth (Symmetric Polynomials on both sides of the threshold)

	3rd order polynomial		4th order polynomial		5th order polynomial	
	Pooled OLS	FE	Pooled OLS	FE	Pooled OLS	FE
GDP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)
Objective 1	.020	.019	.019	.020	.019	.020
	(.002)***	(.004)***	(.002)***	(.004)***	(.002)***	(.004)***
Const.	.046	.070	.068	.088	.109	.113
	(.010)***	(.015)***	(.016)***	(.023)***	(.026)***	(.043)***
Obs.	674	674	674	674	674	674
R^2	.16	.18	.17	.18	.17	.18
Employment growth						
Objective 1	.002	-.004	.002	-.003	.003	-.001
	(.002)	(.003)	(.002)	(.003)	(.002)	(.003)
Const.	-.017	.019	-.011	.023	.051	.086
	(.009)*	(.015)	(.018)	(.026)	(.030)*	(.052)*
Obs.	674	674	674	674	674	674
R^2	.03	.06	.03	.07	.05	.08

Notes: ***, **, *, ♯ denote statistical 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 forced to have identical parameters to the left and the right of the threshold. 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 statistical yearbook.

Table 7: RDD NUTS2 - Objective 1 and GDP per capita/Employment growth (Asymmetric Polynomials on both sides of the threshold)

	3rd order polynomial		4th order polynomial		5th order polynomial	
	Pooled OLS	FE	Pooled OLS	FE	Pooled OLS	FE
GDP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)
Objective 1	.005	.007	.006	.013	.009	.016
	(.003)$^\sharp$	(.004)*	(.004)*	(.004)***	(.003)***	(.004)***
Const.	.02	.02	.02	.03	.06	.05
	(.012)*	(.024)	(.022)	(.053)	(.040)	(.118)
Obs.	674	674	674	674	674	674
R^2	.28	.31	.28	.32	.28	.31
Employment growth						
Objective 1	.003	.006	.004	.003	.006	.004
	(.004)	(.004)	(.004)	(.005)	(.004)	(.004)
Const.	-.039	-.017	-.062	-.069	-.026	.036
	(.008)***	(.021)	(.017)***	(.050)	(.031)	(.100)
Obs.	674	674	674	674	674	674
R^2	.08	.12	.09	.13	.09	.14

Notes: ***, **, *, $\sharp$ denote statistical 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 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 statistical yearbook.

Table 8: Robustness

Type of sensitivity check	GDP/capita growth Coef./(Std.err.)	Obs.	Employment growth Coef./(Std.err.)	Obs.
(I) Effects on NUTS3 regions				
Estimated model as in column (6) of Table 7	.017 (.005)***	3300	.004 (.005)	3300
Estimated model as in column (6) of Table 7 plus additional control variables [a]	.012 (.003)***	3300	-.002 (.002)	3300
(II) Window around GDP/capita threshold (NUTS2 regions) [b]				
60% and 90% of EU average; 3rd order polynomial	.010 (.006)*	248	.002 (.009)	248
60% and 90% of EU average; 2nd order polynomial	.010 (.006)♯	248	.010 (.006)	248
65% and 85% of EU average; 3rd order polynomial	.010 (.004)**	168	.008 (.005)	168
65% and 85% of EU average; 2nd order polynomial	.011 (.005)**	168	.009 (.007)	168
70% and 80% of EU average; 3rd order polynomial	.008 (.004)**	76	0.006 (.007)	76
70% and 80% of EU average; 2nd order polynomial	.011 (.004)***	76	0.006 (.007)	76
(III) Controlling for spillover effects (NUTS2 regions)				
Spatial exclusion mechanism (radius of 150km) [c]	.015 (.004)***	581	.004 (.004)	581
Spatial exclusion mechanism (radius of 200km)	.015 (.004)***	535	.005 (.004)	535
Including a treatment indicator (radius of 150km)[d]	.012 (.003)***	674	.009 (.004)***	674
Including a treatment indicator (radius of 200km)	.013 (.003)***	674	.007 (.004)*	674
(IV) Programming period-specific effects (NUTS2 regions)[e]				
Average growth in period 1989-93	.066 (.038)**	186	-.036 (.021)*	186
Average growth in period 1994-99	.008 (.005)♯	209	.008 (.006)	209
Average growth in period 2000-06	.011 (.006)**	279	-.002 (.006)	279
(V) Average growth effect until how many years after beginning of programming period (NUTS2 regions)[f]				
1 year	.0002 (.005)	604	-.001 (.006)	604
2 years	.0001 (.004)	604	-.002 (.006)	604
3 years	.004 (.004)	604	.004 (.005)	604
4 years	.007 (.004)*	674	.004 (.004)	674
5 years	.003 (.003)*	488	.002 (.005)	488
6 years	.011 (.006)**	279	-.002 (.006)	279

Notes: ***, **, *, ♯ denote statistical significance at the 1%, 5%, 10%, and 15% level, respectively. Standard errors are clustered at the NUTS2 level. First-stage regressions are probit models. Each specification except for the period-specific estimates includes region-specific fixed effects. [a] This sensitivity check includes the employment share, the industry and the service share of total employment, the population size, the population density and the Shapley-Shubik index as further control variables (for descriptive statistics, see table 5). [b] The sample is limited to regions characterized by an initial per-capita GDP within a certain window around the 75% threshold. [c] Untreated units with a treated unit within a radius of 150km or 200km are excluded. [d] An indicator variable is included which is unity if other NUTS2 regions got treated within a radius of 150km or 200km, respectively. [e] Separate samples for each programming period are analyzed. [f] The treatment effect realized after one, two, three etc. years is estimated by adjusting the time horizon of the dependent variable. 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 NUTS3 regions we calculated GDP per capita growth for the years 1989 and 1990 using information from the GDR's statistical yearbook.

Figure 1: Objective 1 regions

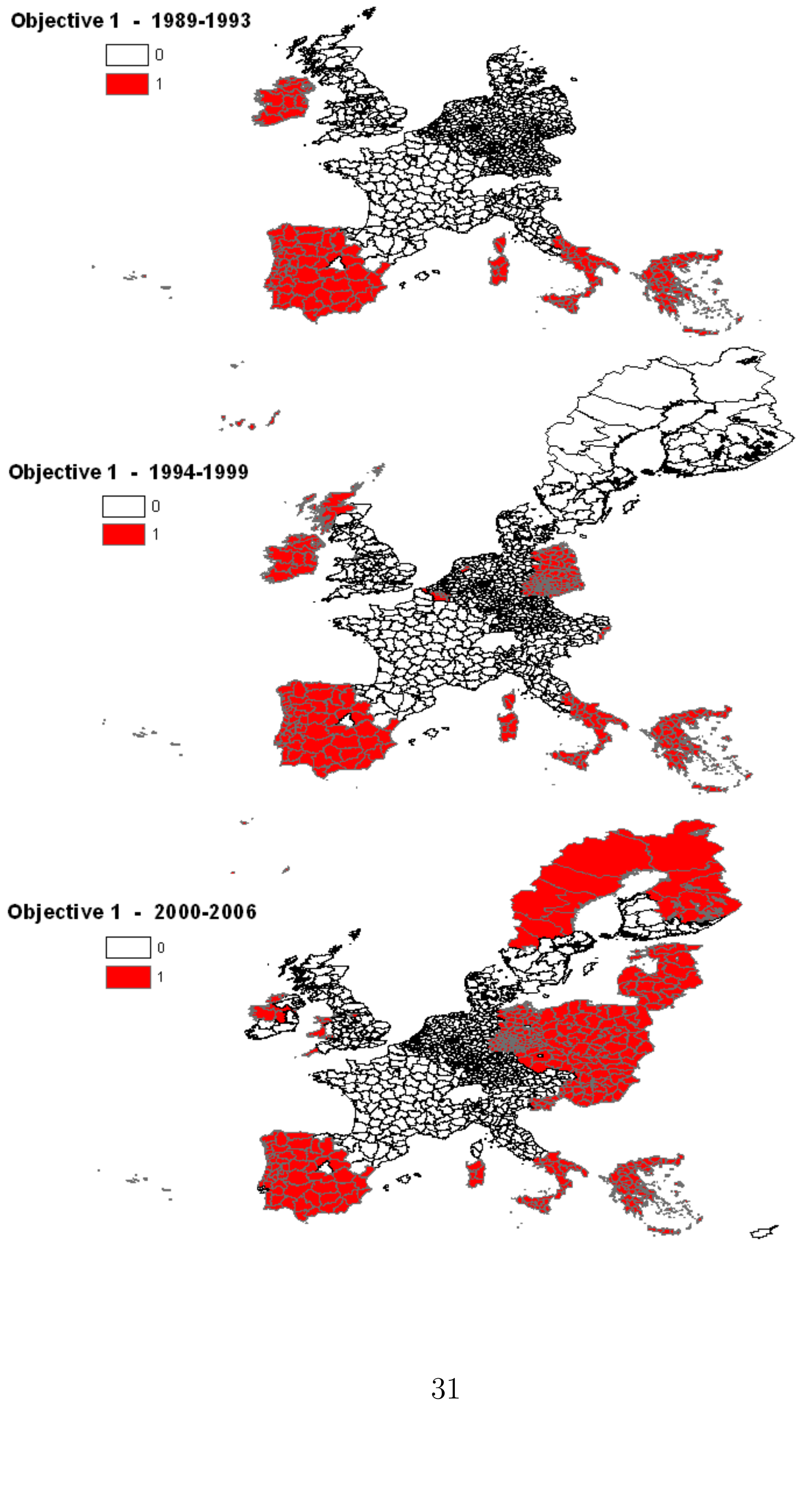
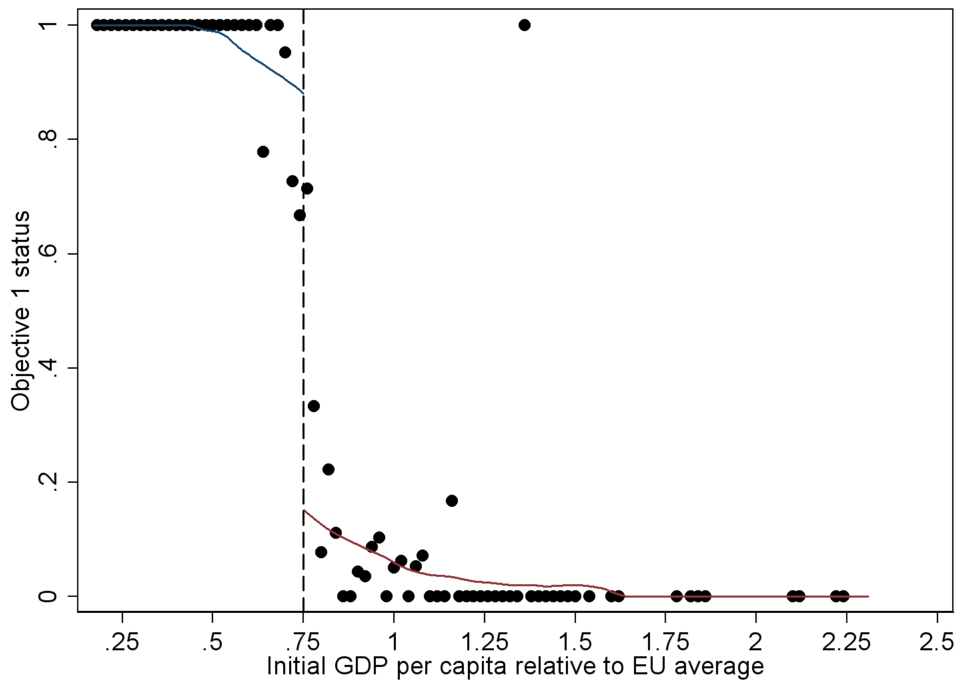
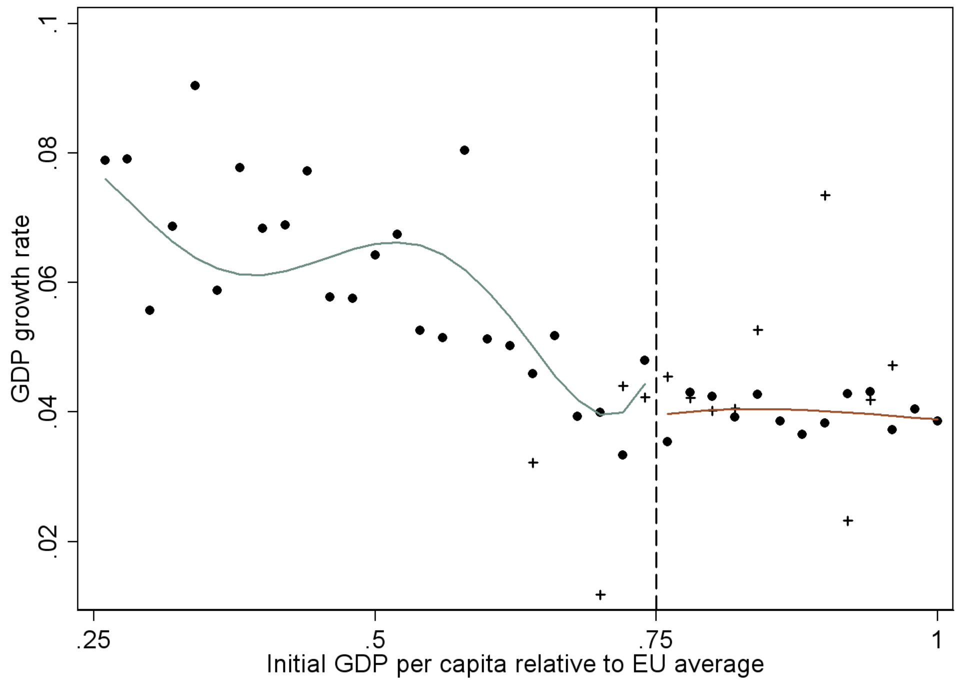


Figure 2: Objective 1 status and the 75% GDP threshold



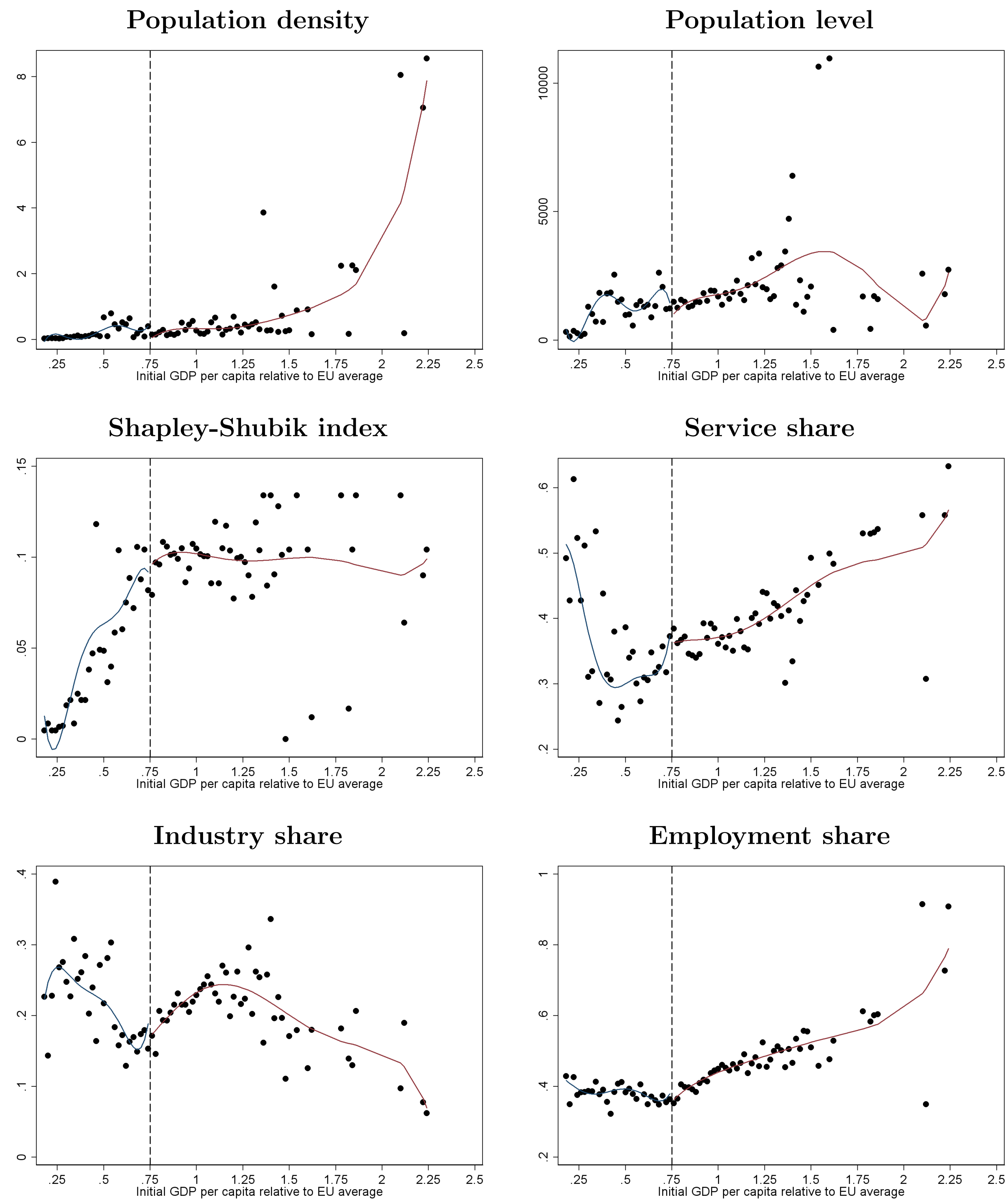
Note: The figure shows average treatment rates in equally sized bins of 2% which are plotted against the per capita GDP that applied in the years relevant for the decision about Objective 1 status. The graph represents a local polynomial smooth; based on Epanechnikov kernel with rule-of-thumb bandwidth. Note that the outlier at about 1.3 times the EU average which received treatment represents only one observation, namely Berlin (West and East combined) in the 1989-1993 programming period. All results are robust to the exclusion of Berlin.

Figure 3: Growth and the 75% GDP threshold



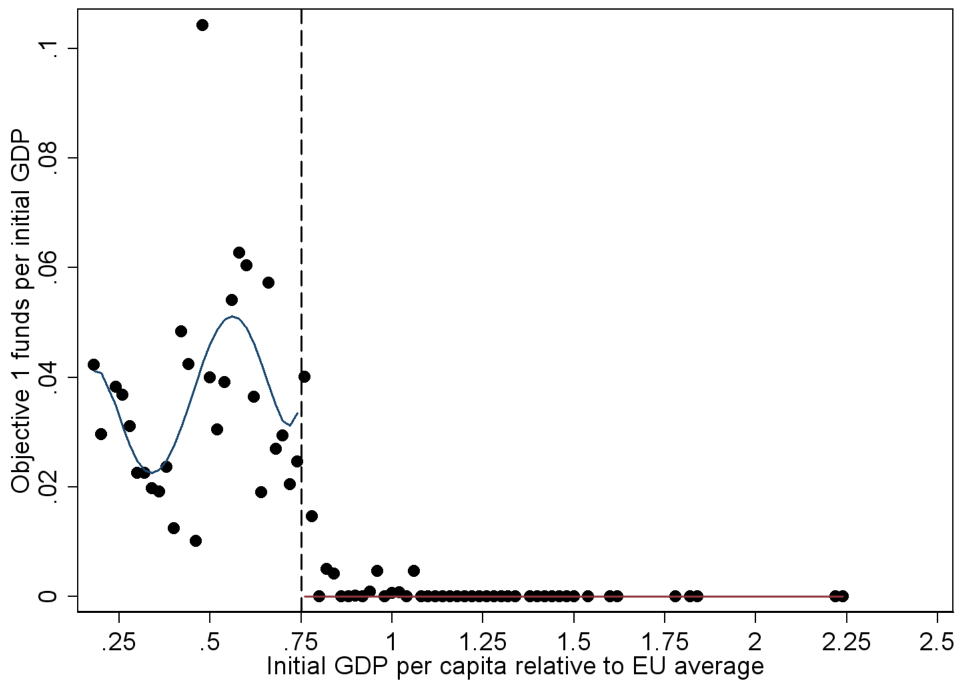
Note: The figure shows averages of GDP per capita growth in equally sized bins of 2% which are plotted against the per capita GDP that applied in the years relevant for the decision about Objective 1 status. Diamonds represent correctly classified observation according to the 75% rule while crosses mark incorrectly classified observations. The graph represents a 5th order polynomial function.

Figure 4: Covariates and the 75% GDP threshold



Note: The figures shows averages of various covariates in equally sized bins of 2% which are plotted against the per capita GDP that applied in the years relevant for the decision about Objective 1 status. The graphs represent a 5th order polynomial function.

Figure 5: Objective 1 Funds per GDP and the 75% GDP threshold



Note: The figure shows averages of Objective 1 payments per GDP in equally sized bins of 2% which are plotted against the per capita GDP that applied in the years relevant for the decision about Objective 1 status. The graph represents a 5th order polynomial function.