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# Effects of EU Regional Policy: 1989-2013*

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**Abstract**

We analyze EU Regional Policy during four programming periods: 1989-1993, 1994-1999, 2000-2006, 2007-2013. When looking at all periods, we focus on the growth, employment and investment effects of Objective 1 treatment status. For the two later periods, we additionally look at the effects of the volume of EU transfers, overall and in sub-categories, on various outcomes. We also analyze whether the concentration of payments across spending categories affects the effectiveness if EU transfers. Finally, we pay attention to the role of EU funding for UK regions given the current debate in the UK.

**Key words:** Regional transfers; Heterogeneous local average treatment effects.
**JEL classification**: C21; O40; H54; R11

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# 1 Introduction

Many national governments and supranational conglomerates such as the European Union run systems of public transfers to subnational regions with the aim of boosting growth, employment and investment in regions that are lagging behind. The British Commissioner for Regional Policy, George Thomson, argued as early as 1973 that regional policy is 'necessary' to help the poorer regions of Europe. The European Union instituted regional transfers based on collective contributions of countries to the common union budget. Countries contribute about 1 per cent of their annual GDP (largely financed by value-added-tax revenues) to the EU budget. The associated transfers are meant to finance investments – mostly in agriculture, infrastructure, and education – in order to provide for a greater equalization of not only national but subnational regional economic performance measured by real per-capita income. In contrast to other federal systems, the EU lacks many dimensions of economic and institutional homogeneity from a common currency to fiscal authority. The general idea of EU transfers – which are labelled *European Agricultural Guarantee Fund* (EAGF) and *European Agricultural Fund for Rural Development* (EAFRD) in the context of agriculture and *Structural Funds* and *Cohesion Fund* in the context of infrastructure, education, and labor markets – is to foster homogeneity across countries and regions in order to make the European Union's system of market integration viable.

While relative to national budgets the Union's common budget is tiny – accounting for only 1 percent of the joint Union GDP, the *Structural and Cohesion Funds* which are the focus of this paper are a major budget line, the second-largest after agricultural expenses. Not surprisingly, research in recent years evaluated the effectiveness of EU regional policy (see, e.g., Becker, Egger, and von Ehrlich, 2010, 2011, 2012 and Pellegrini et al. 2013, 2015). The insights from this earlier work were three, namely that the expenses through the Union's *Structural and Cohesion Funds*

1. induced positive average effects on per-capita income growth in those subnational regions in the EU that lagged behind the EU average;
2. ... but that more expenses did not generally induce proportionately larger effects;
3. ... and that regions respond quite heterogeneously with smaller effects found in ones where the institutions are bad (corruption is high) and where human capital is scarce.

Some limitations of this earlier work, which focused on the programming (or spending) periods 1989-93, 1994-99, and 2000-06, were the data available at the time. Not only are there now more recent data available which permit us to cover the most recent completed programming period, 2007-13, but also more detail is available on

- different expenditure categories (for the periods 2000-06 and 2007-13);
- financial execution (i.e., the granted transfers by the European Commission versus the actual payments made and projects filed; 2007-13);

- regional outcomes other than just per-capita income and employment such as the business (or sector) structure, local labor markets, education/training, patent statistics, employment and wages/salaries.

The main findings of the paper are as follows. Objective 1 transfers do generate additional growth across funded regions in the EU. The effects are somewhat stronger when looking at all four programming periods together, compared to the analysis which looks only at the two most recent programming periods. One might speculate that the financial crisis which materialized during the 2007-2013 period had an effect on the effectiveness of EU regional policy. We do not find effects on employment growth and the total investment rate during 1989-2013, but a positive effect on the public investment rate. Looking at UK Objective 1 regions in particular,[1] we do no find major differences in their successfulness of turning EU Objective 1 money into economic benefits compared to other Objective 1 regions across Europe.

During the last two programming periods, 2000-2006 and 2007-2013 when more outcomes can be measured, we find positive effects of Objective 1 on the total compensation of employees alongside positive employment effects, which suggests that those compensation effects simply reflect higher employment rates, but not wage effects as such. We also find weakly significant positive effects of Objective 1 funding on the growth rate of patent applications, suggesting positive effects on innovation activity in Objective 1 regions.

Looking at the effect of total EU transfer intensity across all fundings programs, i.e. across all Objectives and not just Objective 1, our approach is as follows: we look at how an increase in transfer intensity affects outcomes holding concentration of spending across spending categories constant at different values of the Herfindahl index of spending. When looking at GDP growth, we find that growth effects are smaller when spending is more concentrated as opposed to more evenly spread across spending categories. This is true across all levels of transfer intensity. We also look at the opposite exercise, where we hold the transfer intensity constant and ask how an increase in the concentration of spending of EU transfers affects growth. Our finding is that an increase in transfer concentration (holding transfer intensity constant) is beneficial only when spending is already extremely concentrated (Herfindahl index at the 90th percentile, or at the 75th percentile). In cases where the given transfer concentration is lower, an increase in transfer concentration does not help growth, holding transfer intensity constant. Together these results suggest that most regions will benefit from a more balanced spending across different spending categories as opposed to concentrating spending on singular categories.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 explains the econometric setup. Section 4 describes the data, section 5 presents results on the effects of Objective 1 transfers, section 6 presents results on total EU regional transfers and section 7 discusses and concludes.

[1] This may be of interest in view of the UK referendum on EU membership.

## 2 Earlier research on the effects of EU Regional Policy

Earlier work on the effects of the EU's Regional Policy was mainly devoted to two related questions, namely whether the program had any positive effects on average, and whether these effects were big enough to justify its existence. In view of the mixed results in earlier work, four issues appear important for identification and the quantitative conclusions: (i) whether all funding lines of EU Regional Policy are considered (nearly every NUTS2 region in any programming phase receives *some* funding); (ii) whether the analysis focuses on binary indicators of funding, and disregards the transfer intensity (EU regions differ to a large extent in the funding intensity); (iii) whether the analysis is geared towards estimating average or heterogeneous effects (the recipient regions differ in terms of absorptive capacity); and (iv) whether an attempt was made to make treated and control regions as comparable as possible (since these groups of regions differ in other dimensions than EU Regional Policy treatment, there is some danger that the estimated effects may be confounded).

At the beginning of the debate on the empirical effects of EU Regional Policy, the diagnose was quite skeptical, since linear regressions did not reveal statistically significant positive effects of the program on per-capita-income growth of treated relative to untreated regions conditional on a set of standard drivers of economic growth (see Sala-i-Martin, 1996; Boldrin and Canova, 2001). However, two issues with this evidence emerged. First, while an important part of EU Regional Policy is devised to the convergence objective (formerly Objective 1), not all of the programme is, so that looking for GDP growth effects of *any* line of the funding scheme is not in line with all of the programme's objectives pursued. Second, a focus on binary (whether-or-not) treatment, the average effect of treatment, and assuming quasi-randomization of the treatment effect by conditioning on the drivers of growth in a linear regression framework may not have been sufficient to reveal the causal effects of EU Regional Policy. Third, this evidence was based on a highly aggregated (country) level, where the effects of treatment at the regional level could have been concealed by aggregation bias (with some of the programme's effects being watered down by programme-unrelated changes in untreated regions).

Subsequent research mostly revealed positive effects of the program when deviating from the estimation strategy of earlier work. First, there seemed to be evidence of effects of the programme even at the country level on other outcomes than per-capita-income growth, namely on agglomeration and industry location (see Midelfart-Knarvik and Overman, 2002). Others found, still at the country level, evidence on per-capita-income growth in countries with favorably institutions, when parting with the focus on average overall effects (see Beugelsdijk and Eijffinger, 2005; Ederveen, de Groot and Nahuis, 2006).

Other papers took a sub-national (NUTS1 or NUTS2 level) perspective: Cappelen, Castellacci, Fagerberg and Verspagen (2003) as well as Ederveen, Gorter, de Mooij and Nahuis (2002) detected a significant positive impact of structural funds on regional growth. However, Dall'erba and Gallo (2008) remarked that the evidence was much weaker when taking cross-border spillover effects of the program into account.

We refer the interested reader to Mohl and Hagen (2010) whose Table 1 nicely summa-

rizes further papers in the literature on the impact of structural funds (SF) on economic growth.

Most recently, researchers emphasized the importance of three issues in the context of identification: first, the heterogeneity of regions and the associated proper conditioning on observed regional differences in order to be able to identify causal effects of Structural Funds on outcomes of interest; second, the role of this heterogeneity for the response to treatment itself; and, third, the difference between the convergence (Objective 1) line and the other lines of the program in generating effects on per-capita-income growth or other outcomes.

Becker, Egger and von Ehrlich (2010) were the first to exploit the fact that Objective 1 funding is based on a simple assignment rule which forms the basis of a fuzzy regression-discontinuity design (RDD): NUTS2 regions qualify for Objective 1 funds if their GDP per capita is less than 75% of the EU average. Exploiting this rule, and using data from three programming periods, 1989-1993, 1994-1999, and 2000-2006, they find that Objective 1 recipient regions grow significantly faster than regions just above the 75% threshold. A simple cost-benefit analysis shows that benefits exceed costs. Pellegrini et al. (2013) largely confirm these results using data for two programming periods, 1994-1999, and 2000-2006 and using GDP data from Eurostat as opposed to GDP data from Cambridge Econometrics, as used in Becker et al. (2010).

In later work, Becker, Egger and von Ehrlich (2013) document that the overall success of the Objective 1 program hides considerable heterogeneity across EU regions: regions with low absorptive capacity – proxied by the human capital endowment of the local labour force and by the quality of local government as perceived by citizens in an EU wide survey – grow more slowly than the average recipient region whereas regions with above average absorptive capacity grow faster. Rodríguez-Pose and Di Cataldo (2015) and Rodríguez-Pose and Garcilazo (2015) closely follow the approach of Becker, Egger, and von Ehrlich (2012) and confirm their findings.

Becker Egger and von Ehrlich (2012) consider all funding lines within EU Regional Policy but focus on heterogeneous effects of funding, depending on the funding intensity. Their results support the size of the average effects in Becker, Egger, and von Ehrlich (2010, 2013), but they pointed to the existence of minimum necessary transfers (i.e., a funding intensity below which positive effects on economic growth could not be triggered) and maximum desirable ones (i.e., a funding intensity above which another Euro of funding would result in less than a Euro of GDP generated). The finding of a maximum desirable transfer intensity suggests that some regions may be receiving too much of a good thing. Pellegrini and Cerqua (2015) combine the RDD based on the 75% rule with continuous measures of transfer intensity and also find a maximum desirable transfer amount above which additional funds do not generate additional growth.

In this paper, we go beyond earlier work by extending the analysis in five important dimensions. First, we extend earlier analyses to include also the latest programming period 2007-2013, i.e. our paper covers all four programming periods 1989-2013. When using all 4 programming periods, we concentrate on the effects of Objective 1 status on GDP growth, employment growth, total investment per GDP and public investment per

GDP. Second, we consider various additional outcomes not so far used in the literature: growth in total compensation of employees, growth in total hours worked of employees, growth in number of patent applications, the participation rate in education and training, and payments (i.e. expenses) relative to commitments as a measure of how regions cope with spending the funds committed to them. Third, we analyze, in the same paper, the effectiveness of Objective 1 treatment (binary treatment) as well an analysis of all EU regional policy funding lines (continuous treatment). For the latter, we devise a novel way to display dose-response functions but looking at percentiles of treatment intensities to display marginal effects and corresponding confidence intervals, which we explain further below. Fourth, we take a particular look at the UK's Objective 1 regions, which may be of particular interest in the run-up to the British EU Referendum. Fifth, we look at the effect of the dispersion/concentration of EU transfers on outcomes, using the Herfindahl index across spending categories.[2] This helps us to shed light on the question whether it is wiser for a region to spread transfers across various different spending categories or rather concentrate them on specific causes.

# 3 Notation and econometric model

Let us use indices $j = 1, ..., J$ and $k = 1, ..., K$ to refer to NUTS2-type regions in two different time intervals: while $j$ refers to a region in programming periods 1989-93, 1994-99, 2000-06, and 2007-13, $k$ refers to such regions in 2000-06 and 2007-13. The reason why two sets of indices have to be used for regional units is that the classification scheme of NUTS2 regions changed consecutively over the years. The mentioned programming periods can be connected by slightly aggregating up the universe of underlying regional units, but doing so over the range of four programming periods would lead to unjustifiably large aggregates. Moreover, let us use $p$ to index the four programming periods and $t = 1989, 1993, 2000, 2007$ and $s = 2000, 2007$ to refer to the initial years in the periods $q = 1$ with $p \in \{1, 2, 3, 4\}$ and $q = 2$ with $p \in \{3, 4\}$, respectively. We distinguish between these data-sets including four and two programming periods as only the latter allows for a balanced panel and a more comprehensive list of outcome variables.

Using $\{T_{js}, T_{kt}\}$ to denote a binary or continuous Structural Funds treatment of interest, $\{x_{js}, x_{kt}\}$ for a vector of control variables in logs, and $\{y_{js}, y_{kt}\}$ for economic outcome, we could formulate a regression model of the form

$$y_{ir} = \alpha_q T_{ir} + f_q(x_{ir}) + u_{ir} \quad i = \{j, k\} \quad , r = \{s, t\}, \quad q = 1, 2. \tag{1}$$

[2]The Herfindahl index is a measure of concentration (or dispersion). Concentration or dispersion of activity is an important, endogenous market attribute in industrial economics. There, it is a key determinant of prices or quantities of output, and it is endogenous, as prices and/or quantities sold affect market entry of firms and, hence, industry concentration (see Bresnahan and Reiss, 1991; Ellickson, 2007; or Bronnenberg, Dhar, and Dube, 2009). In that sense, market concentration – e.g., measured by the Herfindahl index – may be understood as an endogenous treatment variable whose effect may be estimated on outcome when properly conditioning on its determinants (see Dufwenberg and Gneezy, 2000).

What we are interested is identifying and estimating $\alpha_q$ as a programming-period-block-specific *local average treatment effect (LATE)* for various outcomes $y_{ir}$.

Treatments of interest to the present study are the following. First, whether a region is treated as an Objective 1-type unit (unity) or not (zero) may be captured by $T_{ir} = \{O_{js}, O_{kt}\}$. The design of Objective 1-type funding is such that $f_q(x_{ir})$ can be modelled as a flexible parametric or nonparametric function of a single covariate $x_{ir}$, namely region-specific per-capita income in purchasing-power units. Second, the actual payments of transfers by the European Commission, a continuous variable, $T_{ir} = \{P_{js}, P_{kt}\}$. Third, the commitments to transfers by the European Commission, a continuous variable, $T_{ir} = \{C_{js}, C_{kt}\}$. When estimating the response to continuous transfers we extent the model by including a measure that captures the distribution of transfers across different expenditure categories. We denote by $C_{ir}$ the Herfindahl index over 12 expenditure categories.

### 3.1 Regression discontinuity design

We identify the response to binary Objective 1 treatment based on a regression discontinuity design. This approach exploits the fact that only NUTS2 regions whose per capita income (in purchasing power parity) falls short of 75 percent of the EU average prior to a programming period are eligible for such transfers. Since exceptions were made with regard to the eligibility criterion we face a fuzzy RDD where the probability of treatment jumps when regional per-capita GDP falls below 75 percent of the EU average:

$$P(T_{ir} = |x_{ir}) = \begin{cases} h_1(\widetilde{x}_{ir}) & \text{if } \widetilde{x}_{ir} \leq 0 \\ h_0(\widetilde{x}_{ir}) & \text{if } \widetilde{x}_{ir} > 0, \end{cases} \tag{2}$$

where $\widetilde{x}_{ir} = x_{ir} - 0.75x_0$ denotes the deviation of regional per-capita GDP from 0.75 times the EU average $x_0$ in the the threshold years.

We estimate the fuzzy RDD in a 2SLS approach where the regression equations are given by:

$$\begin{aligned} y_{ir} &= \alpha_0 + f_0(\widetilde{x}_{ir}) + T_{ir}[\alpha_q + f_1(\widetilde{x}_{ir}) - f_0(\widetilde{x}_{ir})] + \varepsilon_{ir}, \\ T_{ir} &= \gamma_0 + h_0(\widetilde{x}_{ir}) + E_{ir}[\gamma_q + h_1(\widetilde{x}_{ir}) - h_0(\widetilde{x}_{ir})] + \nu_{ir}, \end{aligned} \tag{3}$$

where $E_{ir} = 1[x_{ir} \leqslant 0.75x_0]$ indicates eligibility and $\alpha_q$ denotes the local average treatment effect. In the following we will base this approach on NUTS2 level data.

### 3.2 Generalized propensity score

The second approach bases on NUTS3 level data and identifies responses to continuous Structural Funds treatments. Moreover, we allow for two treatments being the transfer intensity (ratio of EU transfers and initial GDP) $T_{ir}$ and the distribution of transfers across expenditure categories $D_{ir}$. For each treatment dimension we define *potential* treatment levels $T(\hat{\theta})$, $D(\hat{\theta}))$ with $\theta = 10, 25, 50, 75, 90$ corresponding to the percentiles of *realized* treatment levels over all regions. For each region, we may now define the set of potential

outcomes in terms of a *unit-level dose-response* for $\ell = \hat{T}, \hat{D}$ as $Y_{ir}(\ell)$ and the corresponding *average dose-response* as $\mu(\ell) \equiv= E[Y_{ir}(\ell)]$.

We model transfer intensity and transfer distribution of any kind as a function of a vector of covariates, $X_{ir}$, determining $T_{ir}$ and $D_{ir}$.

$$T_{ir} = f_T(X_{ir}, \delta_T) + \varepsilon_{Tir}; \quad D_{ir} = f_D(X_{ri}, \delta_C) + \varepsilon_{Dir}, \tag{4}$$

where $f_T, f_D$ are flexible functions, $\delta_T$ and $\delta_D$ are unknown parameters, and $\varepsilon_{Tir}$ and $\varepsilon_{Dir}$ are disturbances. We observe $X_{ir}$, the realized continuous treatments, and outcomes. Denote any possible vector of exogenous covariates determining treatment by $x$ and define the bivariate conditional joint density of $\hat{T}, \hat{D}$ given $x$ as

$$g(\hat{T}, \hat{D}, x) = f_{T_{ir}, D_{ir}|X_{ir}}(\hat{T}, \hat{D}|x).$$

Then, the generalized propensity score (GPS) is defined as

$$G_{ir} = g(T_{ir}, D_{ir}, X_{ir})$$

with the property that the probability of the observed treatments being equal to some potential treatment combination $\{\hat{T}, \hat{D}\}$ is independent of the covariates in $X_i$ once we condition on the GPS. Accordingly, the treatment status is independent of the outcomes conditional on the GPS under the assumption of weak unconfoundedness. This implies that we need to condition only on one scalar, namely the GPS for region $ir$, in order to remove the selection bias in the unconditional impact of Structural Funds transfers on different outcomes instead of all covariates in the vector $X_i$.

The implementation follows a two step procedure. First, we estimate (4) and compute the GPS $\hat{G_{ir}}$ where we assume a functional form for the density function $g(\cdot)$, namely bivariate normality. Second, we regress outcome $y_{ir}$ on a flexible function of treatments $T_{ir}, D_{ir}$ and $\hat{G_{ir}}$. Using the parameter estimates of the first and second stages we may compute the GPS for potential treatment combinations $\hat{G_{ir}}(\ell)$ as well as the unit dose response $Y_{ir}(\ell)$. Finally, we obtain the average dose response function evaluate at $\ell$ by averaging over regions. Note that we generally ensure common support, which means that we compare only observations with similar levels of predicted transfer intensity and transfer distribution but different realizations of the treatments. Moreover, we perform balancing tests based on Imai and van Dyk (2004) which prove that conditioning on the GPS is sufficient to achieve comparability of regions in the dimensions of interest. For the second stage regressions we identify for each outcome the optimal polynomials of $T_{ir}, D_{ir}$ and $\hat{G_{ir}}$ according to the AIC and BIC. Standard errors are calculated based on a block-bootstrap which accounts for the panel structure of the data. For each of the 500 draws we replicate the first and second stage estimations as well as the selection of common support.

# 4 Data

Earlier research on the consequences of EU Regional Policy on economic outcomes were focused mainly on binary Objective 1 *treatment* and regional average annual growth or

real per-capita GDP as *outcome*. Relative to that, the range of considered outcomes and treatments in this project is larger as will become clear in the following two subsections.

### 4.1 Outcomes used for 1989-2013

- GDP per capita growth
- Employment growth
- Investment per GDP growth
- Public investment per GDP growth

### 4.2 Additional outcomes used in 2000-2013

New outcomes

- Growth in total compensation of employees
- Growth in total hours worked of employees
- Growth in number of patent applications
- Participation rate in education and training
- Payments relative to Commitments

### 4.3 Measures of transfer treatment

The binary Objective 1 treatment indicator variable, $O_{ir}$, can be constructed for all NUTS2 regions and all programming periods 1989-93, 1994-99, 2000-06, and 2007-13.[3] The eligibility of Objective 1 treatment is determined on the basis of NUTS2 real per-capita levels in determined years prior to each programming period. In principal, assignment would be mechanical, as all regions whose real per-capita income falls short of 75% of the EU average are eligible. However, we need to distinguish between eligible and recipient NUTS2 regions, as not all NUTS2 regions are treated in accordance with the European Commission's per-capita income threshold rule. Important reasons for non-compliance with this rule are the following three. First, GDP per capita used to determine eligibility in the relevant reference years was ex post updated and regions that did not qualify for Objective 1 status based on the information available at the time turn out, ex post, to be eligible, or vice versa. Second, there are specific exceptions granted to regions with a low population density and in peripheral locations.[4] Third, there are specific exceptions for

[3] What was called *Objective 1* – the heading concerned with fostering the catching up in real per-capita income of lagging-behind NUTS2 regions – up until the 2000-06 programming periods became *Convergence* objective in the 2007-13 period. We treat these two headings as the same and call them *Objective 1*.

[4] Examples for such recipient regions are NUTS2 regions in northern Sweden and eastern Austria.

individual regions that cannot be explained by the former two arguments.[5] An additional remark relates to 'phasing-out' regions. Those are regions that had been treated in prior programming periods, but are no longer eligible in a given period. They receive some funding to finalize earlier-planned investments, but at a considerably lower level than the previous Objective 1 funding. Note that, in our analysis, we treat phasing-out regions as non-Objective 1 regions. Results are robust to defining phasing-out regions as Objective 1 instead.

Actual transfer payments by the European Commission, $P_{ir}$, to all NUTS3 and NUTS2 regions are available for all programming periods 1994-99, 2000-06, and 2007-13. These actual payments address all objectives pursued by the European Commission such as business support, energy, environment and natural resources, human resources, IT infrastructure and services, research and technology, social infrastructure, technical assistance, tourism and culture, transport infrastructure, and urban and rural regeneration.

Transfer commitments by the European Commission, $C_{ir}$, to all NUTS3 and NUTS2 regions are available for the last two completed programming periods, 2000-06 and 2007-13. A positive difference between committed and actual payments may have economic or political reasons.

### 4.4 Control variables

The aforementioned outcomes are, inter alia, determined by a (NUTS3 or NUTS2) region's initial economic state as captured by its prior-to-programming-period real per-capita income level, other prior-to-programming-period economic characteristics such as the structure of the economy: e.g., the relative importance of employment in agriculture, manufacturing, and various types of services, and programming-period population growth.

### 4.5 Sample composition

The composition of the sample underlying the subsequent analysis will depend on the level of regional aggregation used (NUTS3 versus NUTS2 regions) and the treatment considered (binary Objective 1 treatment versus continuous expenditure or commitment data). The number of NUTS2 regions available after harmonizing data on economic outcome from Cambridge Econometrics and the European Commission's Structural Funds is 187 in 1989-93, 209 in 1994-99, 253 in 2000-06, and 253 in 2007-13. We do not currently include Bulgaria, Romania and Croatia in the analysis. The number of NUTS3 regions available after harmonizing data on economic outcomes from Cambridge Econometrics and the European Commission's Structural Funds is 1,113 in 2000-06 and 1,291 in 2007-13.

### 4.6 Descriptive statistics: NUTS2

Table 1 sheds light on the status of NUTS2 regions in the programming periods 1989-93, 1994-99, 2000-06, and 2007-13 regarding the eligibility for funding under the Objective 1

[5] Examples are Stockholm and Prague as two recipient regions during the programming period 2000-06.

line of the Structural Funds and actual treatment (recipience of funds). While Panel A pools regions over all programming periods so that the numbers refer to region-period observations (one observation represents one NUTS2 region in a single programming period), Panels B-E present the programming-period-specific numbers, with Panels B, C, D, and E, referring to periods 1989-93, 1994-99, 2000-06, and 2007-13, respectively. While it may be interesting for some readers to see the pattern of eligibility versus actual treatment across all programming periods, we suppress such a detailed discussion here for the sake of brevity and focus on the numbers obtained from the pooled data in Panel A. These numbers suggest that of the altogether 1,153 NUTS2-region-period observations covered, 343 were eligible for Objective 1 treatment, while 374 actually got it. Cases where eligible regions did not get Objective 1 treatment are rare (18 out of 343 observations), but treatment in absence of a formal eligibility in terms of the initial-period per-capita-income rule are not infrequent (49 out of 810 cases). This pattern must be attributed to the fact that formal Objective 1 treatment eligibility did guarantee treatment accessibility whenever such eligibility was proven to the European Commission. A key source of lack of this was entirely in the hands of the national governments and rooted in an absence of data on per-capita incomes at the appropriate regional level. Objective 1 treatment in the absence of per-capita-income-rule-based eligibility roots in a number of exceptions that were formulated in the respective budgets – in part, those may be seen as an outcome of lobbying on the part of national governments.

Table A1 summarizes characteristics of key variables of interest to the present analysis, again for data pertaining to NUTS2 regions which are pooled over the four programming periods 1989-93, 1994-99, 2000-06, and 2007-13, akin to Table 1. In a horizontal dimension, the table contains four columns, referring to the mean, the standard deviation, the minimum, and the maximum of values of variables. In a vertical dimension, the table contains three types of variables: outcome (or dependent) variables of interest such as *GDP per capita growth* (measured as the average annual difference of the logarithms of end-of-period and prior-to-period GDP per capita). The prior-to-period years are 1988 for 1989-93, 1993 for 1994-99, 1999 for 2000-06, and 2006 for 2007-13. Employment growth is also defined in terms of logarithms, while *Total investment over GDP* and *Public investment over GDP* are average levels of ratios. Hence, with *GDP per capita growth*, an average of 0.03 indicates an average annual growth rate of about 3 percent. With, e.g., *Total investment over GDP*, an average of 0.23 indicates an average annual investment rate of 23 percent of GDP.

Below the outcome variables, we list the statistics for two binary Objective 1 indicator, one for actual treatment and one for treatment eligibility. These statistics are consistent with the numbers in Table 1. There, an average of 0.31 for *Objective 1* means that 31% of the pooled NUTS2 data across periods represent ones where an observation received actual treatment under the Objective 1(-type) line. As we know, fewer, namely about 28%, observations were actually eligible under the per-capita-income rule.

Below the two binary Objective 1 indicator variables, we report the normalized level of per-capita GDP measured in purchasing power parity in the appropriate years prior to the programming periods. Typically, eligibility was determined based on an average of

this variable in three specific years prior to a programming period.[6] The variable is normalized in order to measure a deviation from the respective EU average. As the minimum and maximum numbers show, the normalized variable may be positive or negative: negative numbers indicate normalized values of by-rule eligible NUTS2 regions, while positive numbers indicate normalized values of by-rule ineligible NUTS2 regions. Bigger absolute values of this variable indicate relatively clearer cases (i.e., regions that are further off the critical cutoff level determining Objective 1 treatment eligibility according to the rule).

Table A2 displays summary statistics for only the last two programming period: 2000-2006 and 2007-2013. In these two periods, we observe additional outcomes compared to earlier programming periods.

### 4.7 Descriptive statistics: NUTS3

Table 8 and Appendix Table A3 summarize important dimensions of Structural Funds payments to NUTS3 regions. On average, NUTS3 regions receive 3 and 4 percent of their GDP from the central EU budget in the periods 2000-2006 and 2007-2013, respectively. The variation is substantial as the maximum payment intensity reached 64 and 46 percent, as can be seen in Table 8. The distribution of payments is measured by the Herfindahl index $D_{ir}$ across the shares of 12 expenditure categories summarized in Table A3. On average expenditure is relatively diversified with $D_{ir}$ ranging between 0.11 and 1.00 and an average of 0.31 in 2000-2006 . The fact that the maximum value of the Herfindahl index is 1 suggests that there are regions which have expenditures fully concentrated on one category. The three most important spending categories, according to Table 8, were *business support*, *transport infrastructure*, and *environment and natural resource* in the first period while in the second period spending on *research and technology* outstripped those on *business support* and *environment and natural resource*.

Appendix Table A3 summarizes characteristics of outcome variables and covariates used in the analysis on NUTS3 level. We consider seven outcomes: *GDP per capita growth*, *employment growth*, *employment rate*, *patents per capita*, *employment share in construction* and *employment share in the public sector*. For the estimates of the GPS we consider all main effects of the covariates listed in Table A3 together with up to 10th order polynomials and all possible interactions of the linear terms.

## 5 Results: Objective 1 treatment

### 5.1 Main findings on the effects of Objective 1 treatment

Table 2 summarizes results based on regression-discontinuity-design (RDD) regressions with (fuzzy) Objective 1 treatment as the explanatory variable of interest and pre-period

[6] These years were 1983-1985, 1988-1990, 1994 -1996 (1997-1999 for new members), 2000-2002 for the four programming periods we consider. See EU Council Regulations 2052/88, 2082/93, 502/1999, 595/2006, and 189/2007.

per-capita income in purchasing-power parity as the so-called forcing variable which determined rule-based treatment. Each panel is horizontally organized in four columns with parameter estimates and statistics. Column (1) pertains to a linear specification in terms of the forcing variable, whereby separate parameters on the linearly entering forcing variable are estimated where normalized, initial-period, real per-capita income negative (so that a NUTS2 region is eligible for Objective 1-type treatment) versus nonnegative (when a NUTS2 region is not eligible for Objective 1-type treatment). Column (2) is the same as Column (1) except that NUTS2 fixed effects across programming periods are included. With dense-enough data – i.e., with sufficiently many Objective 1-type treatment-eligible and -noneligible observations in the neighborhood of a zero normalized pre-period per-capita income – including such fixed effects (or any other control variable) would not be necessary. However, given the limited number of NUTS2 regions at hand, controlling for fixed NUTS2 effects might be desirable. Columns (3) and (4) correspond to Columns (1) and (2), respectively, except that they use linear and quadratic terms of the forcing variable. There, separate parameters on the simple and the squared forcing variable are estimated where normalized, initial-period, real per-capita income negative versus nonnegative, respectively. Hence, while there are two forcing-variable terms in the regressions summarized in Columns (1) and (2), there are four terms in the ones summarized in Columns (3) and (4).

The results in Table 2 be summarized as follows. First, the parameters in Panel A are relatively stable across the four columns of interest, and they vary between 0.012 in Column (3) and 0.019 in Columns (2) and (4). These findings support an increase in period-specific per-capita-income growth by somewhat less than 2 percentage points due to Objective 1 treatment. These results which are obtained across all four covered programming periods are quantitatively close to the findings in Becker, Egger, and von Ehrlich (2010). The fact that including versus excluding the region-specific fixed effects is of little bearing to the statistical (and economic) significance of the results suggests that omitted variables are of minor importance, and the RDD is relatively successful in isolating the causal effect of Objective 1 treatment on per-capita income growth.

This is much less the case for *Employment growth* and total *Investment intensity* in Panels B and C, respectively. There, we find statistically significant effects on employment growth (negative) and investment intensity (positive) only when not controlling for region-specific fixed effects, whereas the impact of Objective 1 treatment is statistically insignificant when accounting for those effects. This suggests that Objective 1 treatment and/or the forcing variable is correlated with time-invariant determinants of employment growth and investment intensity. Hence, we should be more cautious in interpreting the respective effects relative to the ones on per-capita-income growth or on public investment intensity.

### 5.2 Specific Objective 1 treatment effects in the UK

Towards an assessment of the effects of Objective 1 treatment on regions in the UK relative to other regions, we slightly modify the RDD approach. In this context, we are interested

in assessing to which extent the effects on the average NUTS2 region in the UK differ from the ones on the grand-average NUTS2 region in the EU. For that reason, it is useful to create a binary indicator variable which is unity if two conditions are fulfilled at the same time: a NUTS2 region belongs in the UK, and it receives (for the treatment indicator) or is eligible for(regarding the eligibility indicator) Objective 1 treatment. Employing such indicators along with the original ones is inconvenient, since the parameter on the main effect of Objective 1 treatment would then not reflect the local average treatment effect anymore. This situation can be avoided when demeaning the Objective 1-UK interaction effect. Then, the parameter on the main Objective 1 treatment variable measures the local average treatment effect as before (i.e., in Table 2), while the one on the interaction term measures the deviation from this average for UK-borne NUTS2 regions.

Table 3 present the corresponding results and are comparable to Table 2. Table 3 suggests that statistically significant deviations from the EU (local) average are only found when *not* conditioning on fixed NUTS2-region effects. However, the findings also suggest that the magnitude of the point estimate on the Objective 1-treatment-UK interaction terms is not altered much for per-capita income growth or employment growth when including fixed regional effects.

### 5.3 Specific Objective 1 treatment effects on other outcomes

Table 4 repeats the analysis of Table 2 for only the last two programming periods. This serves two purposes: first, it allows us to understand whether effects of Objective 1 transfers are stable over time. Second, it provides benchmark estimates for the main outcomes before we turn to new outcomes which we can only measure in those last two programming periods. The findings in the periods 2000-2006 and 2007-2013 are somewhat different: (a) GDP growth effects are smaller than for the whole period 1989-2013, possibly due to the financial crisis that affected the last programming period, (b) interestingly, there is now a positive effect on employment growth; (c) there is still no effect on the total investment rate, and (d) there is no longer an effect on the public investment rate. Table 6 analyzes whether UK Objective 1 regions differ from the rest of the EU, but this does again not seem to be the case.

Table 5 considers outcomes beyond the ones in Subsection 5.1: *Growth in total compensation of employees*, *Growth in total hours worked of employees*, *Growth in number of patent applications*, *Participation rate in education and training*, and *Payments of EU transfers relative to commitments*.

While these outcome variables had not been considered in earlier work, they deserve some attention for the following reasons. First, Objective 1 treatment provides access to large funds relative to other sources provided by the European Commission. The bureaucratic hurdles regarding application and recipience as well as the monitoring of these funds could differ to an extent that would distort the timing of payments so that in an average year payments could deviate more substantially from commitments than on average. Second, the growth in total hours worked potentially addresses margins of employment adjustment beyond the extensive margin reflected in the head count. If

Objective 1 treatment led to a marginal change in labor supply and demand, it could affect the hours worked without any impact on the number of employed persons. Similarly, Objective 1 treatment could affect the wage bill paid out in a region without affecting the number of employed persons. Finally, Objective 1 treatment might stimulate high-technology investments beyond average investments in a region which might show in higher counts of patent applications, all else equal.

Among these considered outcomes, Objective 1 treatment appears to induce a statistically significant effect which is robust to the inclusion of NUTS2-region fixed effects only on the growth of total compensation of employees and on the growth of patent applications. According to the results in Panel A, the treatment of interest raises the growth of total compensation of employees in a NUTS2 region by about 1.8 percent, which is quantitatively comparable to the increase in employment growth. Hence, these results suggest that the lion's share of the effect on per-capita income appears to flow from adjustments at the extensive employment margin. The boost in the growth of patent applications suggests increased innovation activity as a result of Objective 1 transfers.

# 6 Results: Total EU transfers

## 6.1 Main findings on the effects EU transfers

Figures 1 and 2 illustrate the marginal effects of an increase in the level $P$ and concentration $H$ of total EU transfers, respectively. The marginal effects are evaluated at the $10th$, $25th$, $50th$, $75th$, and $90th$ percentiles of payment intensity and distribution. Each graph is organized in five vertical layers and five colors. The former refer to the percentiles of $P$ while the latter refer to the percentiles of $H$. The bars represent the 90 percent confidence intervals and the dots mark the corresponding point estimates. Figures A1 and A2 follow the same structure but present the marginal effects for a common support sample based on 9 groups. We report in each figure the result for GDP per capita growth, employment growth, avg. annual employment ratio, avg. annual patents per capita, and the avg. annual employment shares of construction and public sector in total employment.

Starting with Figure 1, we find a significant and positive marginal effect of $P$ on per capita growth that ranges between 0.08 and 0.3 percentage points. Hence, an increase of EU transfers per initial GDP (payment intensity) by one percentage point raises avg. annual per capita growth by up to 0.3 percentage points. For each layer of transfer intensity we observe that the marginal effect declines with higher concentration of funds. Moreover, the marginal effect diminishes in the transfer intensity. Note also that the estimates for very low and very high concentration of funds are less precise due to fewer observations at these levels.

This holds also true for employment growth where the point estimates are again only significant for intermediate levels of concentration of funds. Moreover, the point estimates tend to be declining up to the $75th$ percentile of transfer intensity while the increase again somewhat for very high transfer intensity. The magnitude suggests an increase in employment growth between 0.19 and 0.42 percentage points due to an increase of average

annual transfers by one percent of initial GDP.

Consistent with this result we observe a significant increase in the ratio of employment to active population. On average our sample displays an employment rate of 89 percent which increases by up to 2 percentage points due to EU transfers. The employment shares of the public sector and the construction sector are on average 29 and 8 percent, respectively. Interestingly, the transfers seem to have no effect on the size of the local public sector (which may be due to our definition "non-market services" whatever this is) but substantially boost the local share of employment in the construction sector.

Finally, the results with regard to patents per capita suggest a non-monotonic effect. Regions with low transfer intensity tend to shift towards less $R\&D$ intensive activities while we find a significant and positive effect on patents whit very high transfer intensity.

Figure 2 displays effects of marginal increases in spending concentration $H$, holding transfer intensity constant. With regard to GDP per capita growth we find a non-monotonous effect. While the marginal effect of more concentration is close to zero and insignificant for low levels of concentration it even declines for intermediate levels but becomes positive and significant for high levels of concentration. This suggests that conditional on the transfer intensity, funds are more effective when fully concentrated compared to a distribution where transfers are allocated to a few but not many expenditure categories. Using patents per capita as the outcome variable of interest, we find that more concentration has a positive and significant effect for intermediate levels of the Herfindahl index. This is in line with Figure 1 as patents seem to be raised by EU transfer only for a very high transfer intensity which is highly concentrated on expenditure categories relevant for R & D activities. With regard to the other outcomes we observe mostly insignificant effects of the expenditure concentration which suggests that the distribution of transfers is less decisive than the transfer intensity. However, it may still be the case that some expenditure categories are more effective than others as the Herfindahl does not distinguish between concentration in one category (say business support) compared to another (say transport infrastructure).

Figure 3 illustrates the countries that display the highest and lowest usage of the individual expenditure categories compared to the EU average. As is shown in Table 8 about 30 (18) percent of total transfers were allocated to business support (BS) in the 2000-2006 (2007-2013) programming period. The country with the highest appropriation of business support was the UK which deviated by about 22 (15) percentage points from the EU average in the 2000-2006 (2007-2013). Hence, in the average UK NUTS3 region 52 (33) percent of the total EU resources was allocated to business support. On the other end Malta and Estonia allocated the lowest shares to business support. Overall, the variance in expenditure use is substantial. For instance, the share of aggregate expenditure allocated to transport infrastructure exceeds the EU average by 38 and 27 percentage points in Ireland and Poland. Romania invested significantly less in research and technology (RT) and Austria and Denmark use less for transport infrastructure.

## 7 Discussion and conclusions

After agricultural assistance, the European Union's Regional Policy is the second-biggest line in the Union's budget. At times of tighter budgets due to stagnation if not economic downturn, voters and politicians in net-contributing countries and regions ask about the justification of such budgets, even more so than at times of economic prosperity.

This paper sheds light on the effects of the Structural Funds in recipient regions. It illustrates that the programme induced positive effects not only over all periods for which data exist but also in the couple of most recent periods (2000-06 and 2007-13) which were affected adversely by cyclical phenomena. The paper illustrates that the programme's convergence-devised (Objective 1-type) recent effects largely worked through an increase in publicly-funded investments and wages as well as compensation but not through private investment or employment growth.

When considering the programme's objective on a broader scale beyond just per-capita-income convergence, the paper provides novel evidence on the effects of concentrated (across objectives) versus dispersed funding. Specifically, the paper documents that growth effects are smaller when spending is more concentrated on a few lines as opposed to more evenly spread across spending categories on average. This is true across all levels of transfer intensity, i.e., no matter how much funding a region receives overall relative to GDP. However, the effect of the concentration of funding is nonlinear: an increase in transfer concentration at a given level of transfer intensity is beneficial only when spending is already extremely concentrated (at levels of the Herfindahl index at the 75th percentile or at the 90th percentile). At lower levels of transfer concentration raising it does not promote growth ceteris paribus. Hence, on average, regions tend to benefit from a relatively balanced (dispersed) funding of activities, unless they are extremely specialized ex ante.

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

| **1989-2013** | Objective 1 treatment | | |
|---|---|---|---|
| Eligible for Objective 1 | 0 | 1 | Total |
| 0 | 761 | 49 | 810 |
| 1 | 18 | 325 | 343 |
| Total | 779 | 374 | 1153 |
| **1989-1993** | | | |
| 0 | 131 | 9 | 140 |
| 1 | 4 | 43 | 47 |
| Total | 135 | 52 | 187 |
| **1994-1999** | | | |
| 0 | 148 | 14 | 162 |
| 1 | 3 | 44 | 47 |
| Total | 151 | 58 | 209 |
| **2000-2006** | | | |
| 0 | 149 | 12 | 161 |
| 1 | 5 | 87 | 92 |
| Total | 154 | 99 | 253 |
| **2007-2013** | | | |
| 0 | 181 | 2 | 183 |
| 1 | 2 | 68 | 70 |
| Total | 183 | 70 | 253 |

*Notes*: For the first and second programming periods our samples base on the NUTS2 classification from 2003. This yields 187 EU12 NUTS2 regions in 1989-1993 and 209 EU15 NUTS2 regions in 1994-1999. In the last two programming periods our sample bases on the 2006 classification which yields 253 EU25 NUTS2 regions in 2000-2006 and 2007-2013. Phasing-out regions are treated as non-Objective 1 regions. Results are robust to defining phasing-out regions are treated as Objective 1 regions.

Table 2: Effects of Objective 1 treatment – 1989-2013

| | Linear | | 2nd. order polynomial | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **GDP per capita growth** | | | | |
| Objective 1 | 0.013*** | 0.019*** | 0.012*** | 0.019*** |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| Fixed effects | no | yes | no | yes |
| Observations | 901 | 901 | 901 | 901 |
| No. regions | 259 | 259 | 259 | 259 |
| F first-stage | 689.104 | 140.088 | 477.942 | 133.942 |
| AIC | -5182.407 | -5463.379 | -5194.106 | -5464.468 |
| **Employment growth** | | | | |
| Objective 1 | -0.005** | 0.005 | -0.008*** | 0.003 |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| Fixed effects | no | yes | no | yes |
| Observations | 901 | 901 | 901 | 901 |
| No. regions | 259 | 259 | 259 | 259 |
| F first-stage | 689.104 | 140.088 | 477.942 | 133.942 |
| AIC | -5208.505 | -5566.503 | -5202.542 | -5607.387 |
| **Investment per GDP** | | | | |
| Objective 1 | 0.043*** | -0.002 | 0.033*** | -0.002 |
| | (0.009) | (0.017) | (0.011) | (0.017) |
| Fixed effects | no | yes | no | yes |
| Observations | 901 | 901 | 901 | 901 |
| No. regions | 259 | 259 | 259 | 259 |
| F first-stage | 689.104 | 140.088 | 477.942 | 133.942 |
| AIC | -2736.250 | -3615.999 | -2740.356 | -3614.497 |
| **Public investment per GDP** | | | | |
| Objective 1 | 0.037*** | 0.022** | 0.034*** | 0.022** |
| | (0.004) | (0.009) | (0.005) | (0.009) |
| Fixed effects | no | yes | no | yes |
| Observations | 740 | 740 | 740 | 740 |
| No. regions | 252 | 252 | 252 | 252 |
| F first-stage | 481.554 | 95.405 | 362.836 | 94.245 |
| AIC | -3630.509 | -4192.137 | -3644.522 | -4197.942 |

*Notes*: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively. All estimates base on a two-stage least square approach using eligibility as the instrument and controlling for the forcing variable and its interactions . Growth rates refer to log differences divided by the number of years. Investment rates refer to the sum of investments divided by the sum of GDP over the respective programming period. Lower AIC indicates better model-fit.

Table 3: Effects of Objective 1 treatment in the UK – 1989-2013

| | Linear | | 2nd. order polynomial | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **GDP per capita growth** | | | | |
| Objective 1 | 0.013*** | 0.020*** | 0.012*** | 0.020*** |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| UK dev. from EU avg. Obj. 1 effect | -0.012** | -0.013 | -0.013** | -0.014 |
| | (0.006) | (0.012) | (0.006) | (0.012) |
| Fixed effects | no | yes | no | yes |
| Observations | 901 | 901 | 901 | 901 |
| No. regions | 259 | 259 | 259 | 259 |
| AIC | -5177.432 | -5459.069 | -5190.660 | -5460.084 |
| **Employment growth** | | | | |
| Objective 1 | -0.005* | 0.004 | -0.008*** | 0.002 |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| UK dev. from EU avg. Obj. 1 effect | 0.018*** | 0.015 | 0.018*** | 0.010 |
| | (0.006) | (0.011) | (0.006) | (0.011) |
| Fixed effects | no | yes | no | yes |
| Observations | 901 | 901 | 901 | 901 |
| No. regions | 259 | 259 | 259 | 259 |
| AIC | -5212.013 | -5550.788 | -5204.782 | -5597.455 |
| **Investment per GDP** | | | | |
| Objective 1 | 0.041*** | -0.003 | 0.032*** | -0.003 |
| | (0.009) | (0.017) | (0.011) | (0.017) |
| UK dev. from EU avg. Obj. 1 effect | -0.058*** | 0.015 | -0.059*** | 0.015 |
| | (0.022) | (0.034) | (0.022) | (0.034) |
| Fixed effects | no | yes | no | yes |
| Observations | 901 | 901 | 901 | 901 |
| No. regions | 259 | 259 | 259 | 259 |
| AIC | -2747.832 | -3612.189 | -2752.125 | -3610.751 |
| **Public investment per GDP** | | | | |
| Objective 1 | 0.038*** | 0.023** | 0.036*** | 0.023** |
| | (0.004) | (0.010) | (0.005) | (0.010) |
| UK dev. from EU avg. Obj. 1 effect | -0.034*** | -0.009 | -0.034*** | -0.006 |
| | (0.009) | (0.016) | (0.009) | (0.016) |
| Fixed effects | no | yes | no | yes |
| Observations | 740 | 740 | 740 | 740 |
| No. regions | 252 | 252 | 252 | 252 |
| AIC | -3635.270 | -4183.694 | -3650.878 | -4192.463 |

*Notes*: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively. All estimates base on a two-stage least square approach using eligibility as the instrument and controlling for the forcing variable and its interactions . Growth rates refer to log differences divided by the number of years. Investment rates refer to the sum of investments divided by the sum of GDP over the respective programming period. Lower AIC indicates better model-fit.

Table 4: Effects of Objective 1 treatment (I) – 2000-2013

| | Linear | | 2nd. order polynomial | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **GDP per capita growth** | | | | |
| Objective 1 | 0.006*** | 0.012* | 0.005* | 0.012** |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| No. regions | 253 | 253 | 253 | 253 |
| AIC | -3022.157 | -3271.642 | -3028.902 | -3344.430 |
| **Employment growth** | | | | |
| Objective 1 | 0.006** | 0.019*** | 0.003 | 0.017*** |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| No. regions | 253 | 253 | 253 | 253 |
| AIC | -3047.726 | -3323.749 | -3055.183 | -3351.848 |
| **Investment per GDP** | | | | |
| Objective 1 | 0.007 | 0.010 | 0.004 | 0.008 |
| | (0.008) | (0.009) | (0.010) | (0.009) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| No. regions | 253 | 253 | 253 | 253 |
| AIC | -1758.079 | -2846.211 | -1757.593 | -2846.036 |
| **Public investment per GDP** | | | | |
| Objective 1 | 0.016*** | -0.002 | 0.016*** | -0.002 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Fixed effects | no | yes | no | yes |
| Observations | 274 | 250 | 274 | 250 |
| No. regions | 149 | 149 | 149 | 149 |
| AIC | -1694.864 | -2028.886 | -1694.588 | -2029.357 |

*Notes*: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively. All estimates base on a two-stage least square approach using eligibility as the instrument and controlling for the forcing variable and its interactions . Growth rates refer to log differences divided by the number of years. Investment rates refer to the sum of investments divided by the sum of GDP over the respective programming period. Lower AIC indicates better model-fit.

Table 5: Effects of Objective 1 treatment (II) – 2000-2013

| | Linear | | 2nd. order polynomial | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Growth in total compensation of employees** | | | | |
| Objective 1 | 0.005* | 0.018*** | 0.002 | 0.016*** |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| No. regions | 253 | 253 | 253 | 253 |
| AIC | -2985.041 | -3250.432 | -2987.406 | -3277.327 |
| **Growth in total hours worked of employees** | | | | |
| Objective 1 | 0.007** | 0.001 | 0.004 | 0.000 |
| | (0.003) | (0.007) | (0.003) | (0.007) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| No. regions | 253 | 253 | 253 | 253 |
| AIC | -2898.535 | -3127.762 | -2911.118 | -3130.716 |
| **Growth in number of patent applications** | | | | |
| Objective 1 | 0.020 | 0.111* | 0.022 | 0.104 |
| | (0.023) | (0.062) | (0.028) | (0.064) |
| Fixed effects | no | yes | no | yes |
| Observations | 480 | 474 | 480 | 474 |
| No. regions | 243 | 243 | 243 | 243 |
| AIC | -783.547 | -1009.083 | -783.512 | -1010.097 |
| **Participation rate in education & training** | | | | |
| Objective 1 | -0.001 | -0.010 | -0.004 | -0.011 |
| | (0.004) | (0.011) | (0.005) | (0.011) |
| Fixed effects | no | yes | no | yes |
| Observations | 475 | 454 | 475 | 454 |
| No. regions | 248 | 248 | 248 | 248 |
| AIC | -2308.919 | -2460.413 | -2311.384 | -2460.681 |
| **Payments/Commitments** | | | | |
| Objective 1 | -0.009 | 0.025 | -0.014 | 0.021 |
| | (0.016) | (0.037) | (0.019) | (0.038) |
| Fixed effects | no | yes | no | yes |
| Observations | 497 | 488 | 497 | 488 |
| No. regions | 253 | 253 | 253 | 253 |
| AIC | -1111.649 | -1376.100 | -1111.154 | -1374.485 |

*Notes*: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively. All estimates base on a two-stage least square approach using eligibility as the instrument and controlling for the forcing variable and its interactions. Growth rates refer to log differences divided by the number of years. Lower AIC indicates better model-fit.

Table 6: Effects of Objective 1 treatment in the UK (I) – 2000-2013

| | Linear | | 2nd. order polynomial | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **GDP per capita growth** | | | | |
| Objective 1 | 0.006*** | 0.012** | 0.006* | 0.012** |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| UK dev. from EU avg. Obj. 1 effect | -0.001 | -0.006 | -0.001 | -0.007 |
| | (0.005) | (0.015) | (0.005) | (0.014) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| AIC | -3020.067 | -3271.576 | -3026.953 | -3343.203 |
| **Employment growth** | | | | |
| Objective 1 | 0.006** | 0.020*** | 0.003 | 0.017*** |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| UK dev. from EU avg. Obj. 1 effect | 0.009** | -0.016 | 0.010** | -0.016 |
| | (0.005) | (0.015) | (0.005) | (0.014) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| AIC | -3049.622 | -3329.024 | -3055.529 | -3355.676 |
| **Investment per GDP** | | | | |
| Objective 1 | 0.007 | 0.010 | 0.004 | 0.008 |
| | (0.008) | (0.009) | (0.010) | (0.009) |
| UK dev. from EU avg. Obj. 1 effect | -0.004 | -0.013 | -0.004 | -0.013 |
| | (0.017) | (0.024) | (0.017) | (0.023) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| AIC | -1756.271 | -2844.728 | -1755.830 | -2844.650 |
| **Public investment per GDP** | | | | |
| Objective 1 | 0.001 | 0.004 | 0.002 | 0.003 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| UK dev. from EU avg. Obj. 1 effect | 0.032*** | -0.038*** | 0.032*** | -0.037*** |
| | (0.005) | (0.007) | (0.005) | (0.007) |
| Fixed effects | no | yes | no | yes |
| Observations | 274 | 250 | 274 | 250 |
| AIC | -1757.186 | -2038.005 | -1767.265 | -2040.540 |

*Notes*: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively. All estimates base on a two-stage least square approach using eligibility as the instrument and controlling for the forcing variable and its interactions . Growth rates refer to log differences divided by the number of years. Investment rates refer to the sum of investments divided by the sum of GDP over the respective programming period. Lower AIC indicates better model-fit.

Table 7: Effects of Objective 1 treatment in the UK (II) – 2000-2013

| | Linear | | 2nd. order polynomial | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Growth in total compensation of employees** | | | | |
| Objective 1 | 0.004* | 0.018*** | 0.002 | 0.016*** |
| | (0.002) | (0.006) | (0.003) | (0.006) |
| UK dev. from EU avg. Obj. 1 effect | 0.009* | -0.011 | 0.009* | -0.011 |
| | (0.005) | (0.016) | (0.005) | (0.015) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| AIC | -2985.229 | -3252.954 | -2986.388 | -3278.683 |
| **Growth in total hours worked of employees** | | | | |
| Objective 1 | 0.007** | 0.001 | 0.004 | 0.000 |
| | (0.003) | (0.007) | (0.003) | (0.007) |
| UK dev. from EU avg. Obj. 1 effect | 0.006 | 0.011 | 0.006 | 0.011 |
| | (0.005) | (0.018) | (0.005) | (0.018) |
| Fixed effects | no | yes | no | yes |
| Observations | 506 | 506 | 506 | 506 |
| AIC | -2898.057 | -3124.450 | -2909.387 | -3127.824 |
| **Growth in number of patent applications** | | | | |
| Objective 1 | 0.022 | 0.112* | 0.024 | 0.105 |
| | (0.023) | (0.064) | (0.028) | (0.065) |
| UK dev. from EU avg. Obj. 1 effect | -0.023 | -0.012 | -0.024 | -0.009 |
| | (0.042) | (0.140) | (0.042) | (0.140) |
| Fixed effects | no | yes | no | yes |
| Observations | 480 | 474 | 480 | 474 |
| AIC | -780.996 | -1006.778 | -780.938 | -1007.858 |
| **Participation rate in education & training** | | | | |
| Objective 1 | -0.002 | -0.013 | -0.005 | -0.015 |
| | (0.004) | (0.010) | (0.005) | (0.011) |
| UK dev. from EU avg. Obj. 1 effect | 0.011 | 0.074*** | 0.011 | 0.075*** |
| | (0.008) | (0.026) | (0.008) | (0.026) |
| Fixed effects | no | yes | no | yes |
| Observations | 475 | 454 | 475 | 454 |
| AIC | -2305.982 | -2484.357 | -2307.705 | -2483.871 |
| **Payments/Commitments** | | | | |
| Objective 1 | -0.008 | 0.027 | -0.013 | 0.024 |
| | (0.016) | (0.037) | (0.019) | (0.038) |
| UK dev. from EU avg. Obj. 1 effect | -0.021 | -0.236** | -0.021 | -0.234** |
| | (0.031) | (0.095) | (0.031) | (0.095) |
| Fixed effects | no | yes | no | yes |
| Observations | 497 | 488 | 497 | 488 |
| AIC | -1109.784 | -1379.041 | -1109.395 | -1377.860 |

*Notes*: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively. All estimates base on a two-stage least square approach using eligibility as the instrument and controlling for the forcing variable and its interactions. Growth rates refer to log differences divided by the number of years. Lower AIC indicates better model-fit.

Table 8: Distribution of transfers – 2000-2013

| | Mean | StdDev | Min | Max |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Total expenditure per initial GDP (2000-2006) | .005 | .008 | 1.73e-06 | .09 |
| Total expenditure per initial GDP (2007-2013) | .005 | .01 | 5.49e-07 | .07 |
| Share of regions receiving transfers (2000-2006) | .77 | | | |
| Share of regions receiving transfers (2007-2013) | .99 | | | |
| Distribution of expenditure (2000-2006) | .26 | .18 | .00 | 1.00 |
| Distribution of expenditure (2007-2013) | .30 | .15 | .00 | 1.00 |
| **Shares of expenditure category in total transfers** | | | | |
| **2000-2006** | | | | |
| *business support* | .30 | .21 | .00 | 1.00 |
| *energy* | .009 | .02 | .00 | .23 |
| *environment and natural resource* | .12 | .15 | .00 | .98 |
| *human resources* | .04 | .07 | .00 | .89 |
| *IT infrastructure and services* | .03 | .04 | .00 | .36 |
| *research and technology* | .07 | .10 | .00 | 1.00 |
| *social infrastructure* | .03 | .05 | .00 | .60 |
| *technical assistance* | .03 | .05 | .00 | 1.00 |
| *tourism and culture* | .10 | .11 | .00 | .89 |
| *transport infrastructure* | .16 | .18 | .00 | .93 |
| *urban and rural regeneration* | .11 | .12 | .00 | .95 |
| **2007-2013** | | | | |
| *business support* | .18 | .17 | 0 | 1.00 |
| *energy* | .06 | .08 | 0 | .68 |
| *environment and natural resource* | .12 | .13 | 0 | .96 |
| *human resources* | .03 | .08 | 0 | .79 |
| *IT infrastructure and services* | .04 | .06 | 0 | .71 |
| *other* | .002 | .02 | 0 | .39 |
| *research and technology* | .24 | .21 | 0 | 1.00 |
| *social infrastructure* | .04 | .07 | 0 | 1.00 |
| *technical assistance* | .03 | .07 | 0 | 1.00 |
| *tourism and culture* | .06 | .09 | 0 | .82 |
| *transport infrastructure* | .14 | .19 | 0 | 1.00 |
| *urban and rural regeneration* | .05 | .10 | 0 | .96 |

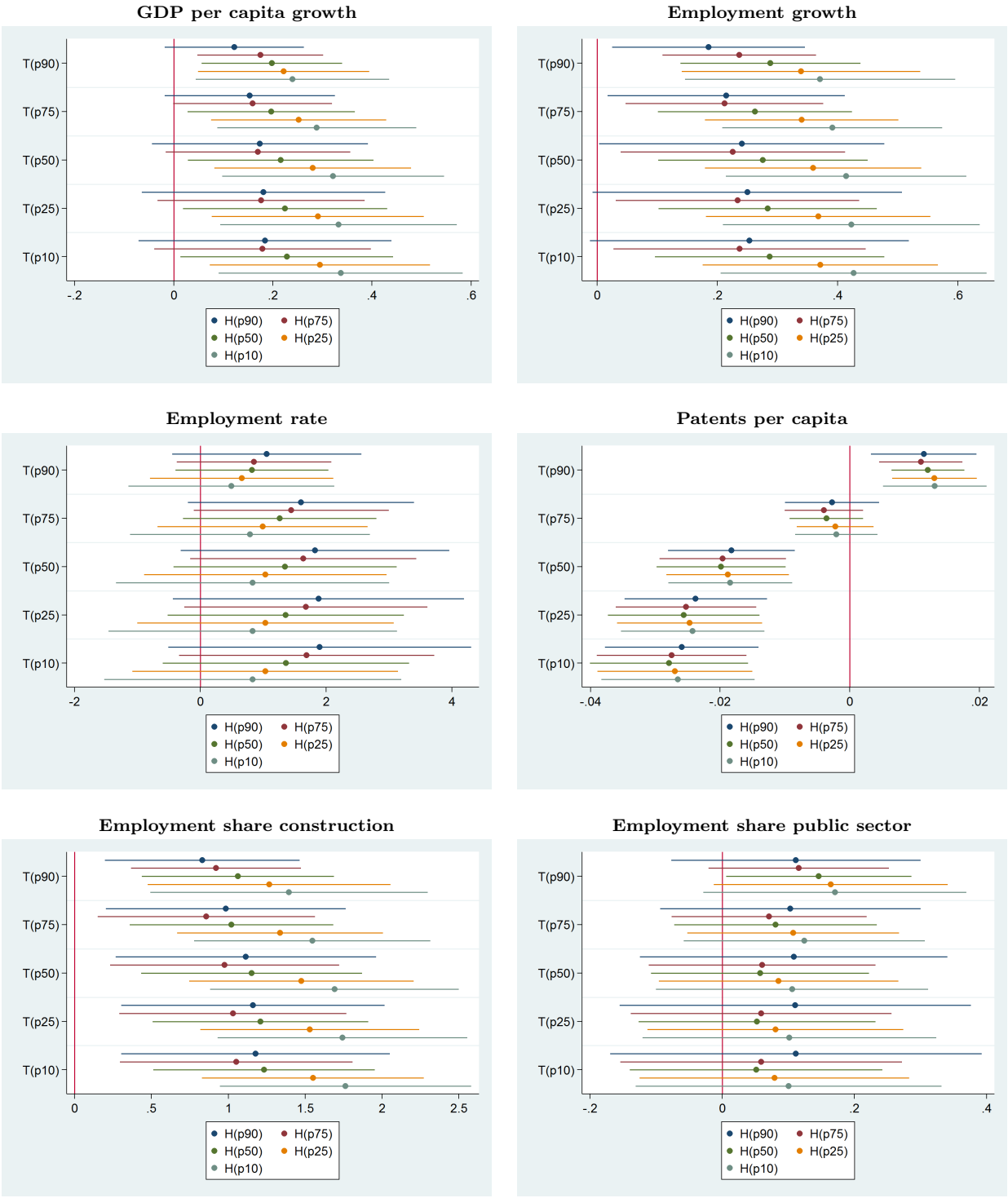
*Notes*: Transfer intensity is defined as total expenditure over all Structural and Cohesion Fund transfers as a share of GDP in the initial year of the respective programming phase. The aggregation in expenditure categories follows EU Commission (2015) 'Geography of Expenditure, Final Report, Work Package 13' (Table 18). For the period 2007-2013 a category *other* includes expenditure priorities 82,83,84 which refer to general *additional costs* hindering the outermost regions' development. This category receives significant amounts (> 5 percent) only in the french oversee départements, the Azores, Madeira, and the Canary islands.

Table 9: Distribution of transfers in the UK – 2000-2013

| | Mean | StdDev | Min | Max |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Total expenditure per initial GDP (2000-2006) | .002 | .001 | .0000181 | .007 |
| Total expenditure per initial GDP (2007-2013) | .0005 | .0009 | 2.63e-06 | .005 |
| Share of regions receiving transfers (2000-2006) | .77 | | | |
| Share of regions receiving transfers (2007-2013) | 1 | | | |
| Distribution of expenditure (2000-2006) | .33 | .25 | .00 | .84 |
| Distribution of expenditure (2007-2013) | .34 | .12 | .15 | .99 |
| **Shares of expenditure category in total transfers** | | | | |
| **2000-2006** | | | | |
| *business support* | .56 | .22 | .13 | .91 |
| *energy* | .005 | .02 | .00 | .13 |
| *environment and natural resource* | .01 | .03 | .00 | .20 |
| *human resources* | .06 | .09 | .00 | .64 |
| *IT infrastructure and services* | .04 | .03 | .00 | .15 |
| *research and technology* | .06 | .05 | .00 | .32 |
| *social infrastructure* | .02 | .02 | .00 | .17 |
| *technical assistance* | .02 | .02 | .00 | .08 |
| *tourism and culture* | .06 | .06 | .00 | .28 |
| *transport infrastructure* | .05 | .09 | .00 | .34 |
| *urban and rural regeneration* | .12 | .12 | .00 | .41 |
| **2007-2013** | | | | |
| *business support* | .32 | .19 | .00 | .69 |
| *energy* | .05 | .08 | .00 | .32 |
| *environment and natural resource* | .06 | .09 | .00 | .48 |
| *human resources* | .04 | .09 | .00 | .37 |
| *IT infrastructure and services* | .05 | .09 | .00 | .71 |
| *other* | .00 | .00 | .00 | .00 |
| *research and technology* | .30 | .19 | .01 | 1.00 |
| *social infrastructure* | .004 | .02 | .00 | .18 |
| *technical assistance* | .02 | .02 | .00 | .14 |
| *tourism and culture* | .05 | .10 | .00 | .48 |
| *transport infrastructure* | .04 | .08 | .00 | .54 |
| *urban and rural regeneration* | .06 | .10 | .00 | .56 |

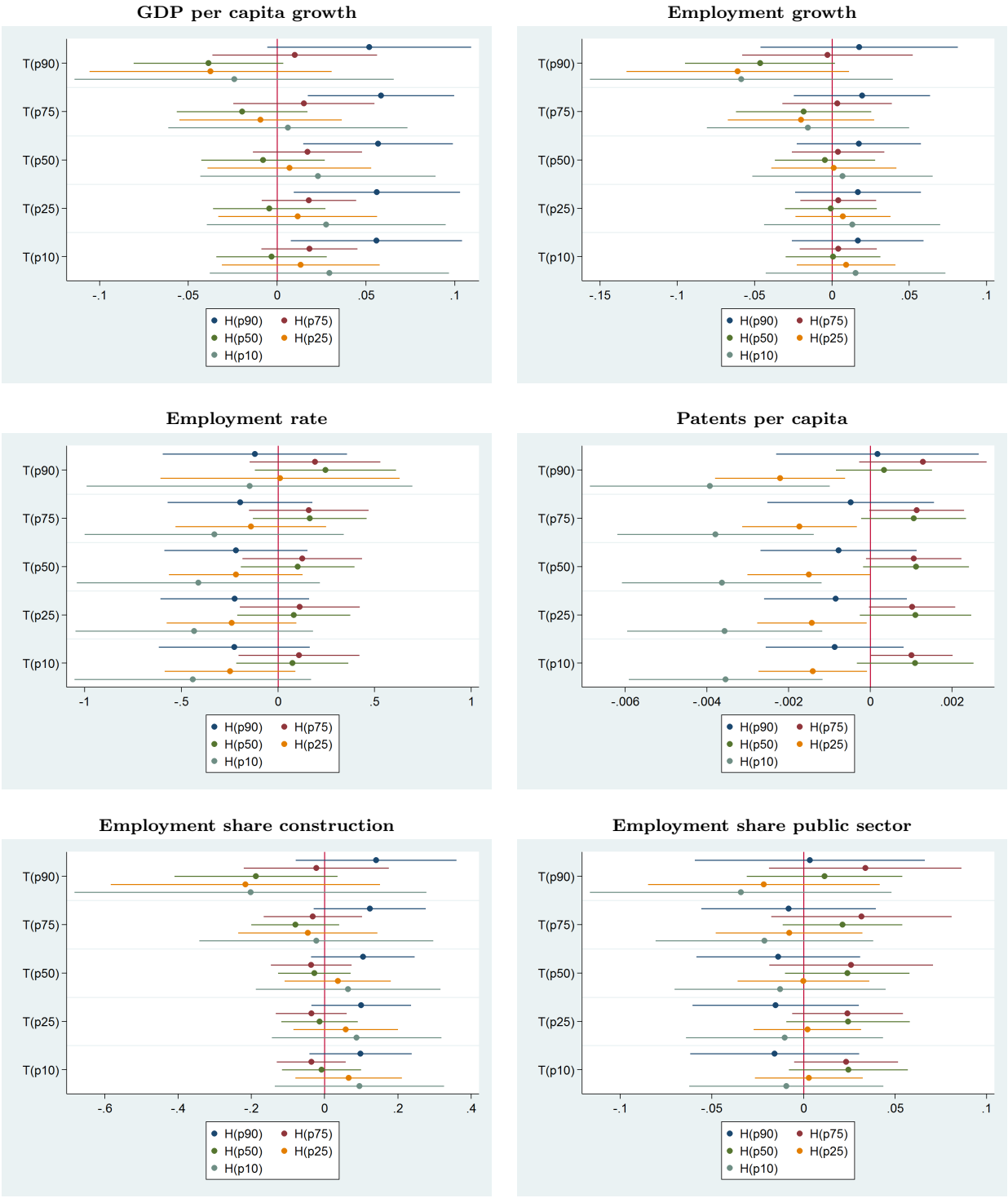
*Notes*: Transfer intensity is defined as total expenditure over all Structural and Cohesion Fund transfers as a share of GDP in the initial year of the respective programming phase. The aggregation in expenditure categories follows EU Commission (2015) 'Geography of Expenditure, Final Report, Work Package 13' (Table 18). For the period 2007-2013 a category *other* includes expenditure priorities 82,83,84 which refer to general *additional costs* hindering the outermost regions' development. This category does not apply in the UK.

Figure 1: Marginal effect of increase in transfer intensity $T$ holding transfer concentration $H$ constant (16 Groups)



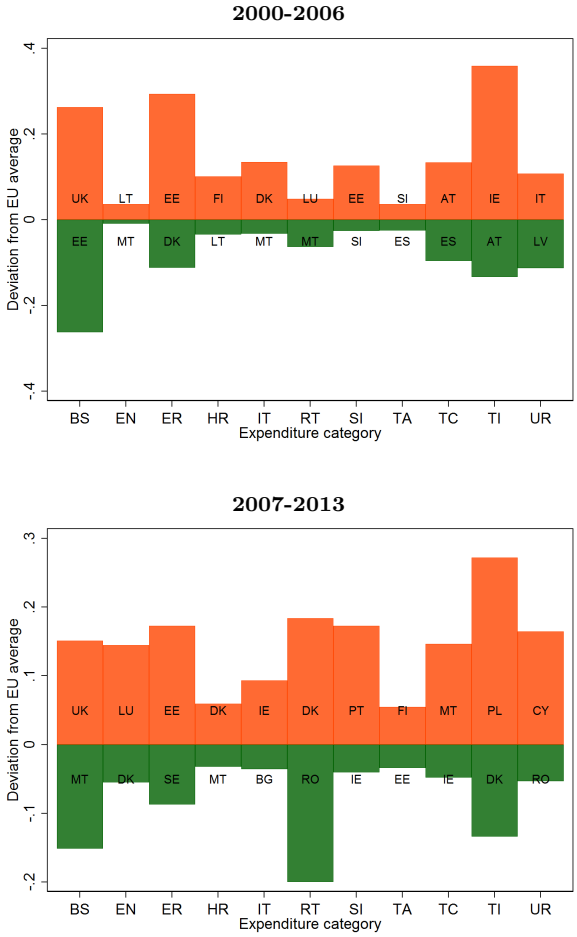

*Notes*: The vertical layers in each graph refer to the percentiles $10, 25, 50, 75, 90$ of transfer intensity ($T$). The colors refer to the corresponding percentiles of transfer concentration across the 12 expenditure categories $H$. We measure the marginal effects on all outcomes in percentage points. To compute these marginal effects we raise transfer intensity (avg. annual transfers per initial GDP) by one percentage point. The dots illustrate the point estimates and the bars display the corresponding 90 percent confidence intervals. We base the sample on observations that satisfy the common support criterion based on 16 groups.

Figure 2: Marginal effect of increase in transfer concentration $H$ holding transfer intensity $T$ constant (16 Groups)




*Notes*: The vertical layers in each graph refer to the percentiles $10, 25, 50, 75, 90$ of transfer intensity ($T$). The colors refer to the corresponding percentiles of transfer concentration across the 12 expenditure categories $H$. We measure the marginal effects on all outcomes in percentage points. To compute these marginal effects we raise Herfindahl index by 0.01 times the standard deviation of the samples Herfindahl index. The dots illustrate the point estimates and the bars display the corresponding 90 percent confidence intervals. We base the sample on observations that satisfy the common support criterion based on 16 groups.

Figure 3: Countries by maximum/minimum deviation from avg. EU expenditure by category




*Notes*: The vertical bars refer to the deviation of the expenditure share from the EU expenditure share of the respective category. We illustrate these deviations for the countries with the maximum and minimum deviations. To obtain the country expenditure shares we take the averages of the expenditure shares in the NUTS3 regions of the respective country. The EU averages are summarized in Table 7. The expenditure categories are 'Business support' (BS), 'Energy' (EN), 'Environment and natural resources' (ER), 'Human resources' (HR), 'IT infrastructure and services', 'Research and Technology' (RT), 'Social infrastructure' (SI), 'Technical assistance' (TA), 'Tourism & Culture' (TC), 'Transport infrastructure' (TI), 'Urban and rural regeneration' (UR).

# Appendix

Table A1: Descriptive statistics NUTS2 – 1989-2013

| | Mean | StdDev | Min | Max |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| GDP per capita growth | .03 | .02 | -.06 | .13 |
| Employment growth | .006 | .02 | -.08 | .07 |
| Total investment over GDP | .23 | .06 | .11 | .62 |
| Public investment over GDP | .03 | .04 | 1.63e-08 | .27 |
| Objective 1 | .31 | .46 | .00 | 1.00 |
| Eligible for Objective 1 | .28 | .45 | .00 | 1.00 |
| GDP per capita minus 75% of EU average | 2790.60 | 5479.27 | -8851.53 | 40895.61 |

Table A2: Descriptives NUTS2 – 2000-2006

| | Mean | StdDev | Min | Max |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| GDP per capita growth | .01 | .02 | -.06 | .11 |
| Employment growth | .006 | .01 | -.03 | .07 |
| Total investment over GDP | .22 | .05 | .11 | .46 |
| Public investment over GDP | .04 | .01 | .02 | .11 |
| Payments over commitments | .85 | .15 | .34 | 1.08 |
| Participation rate in ed and training | .10 | .07 | .006 | .30 |
| Growth total hours worked of employees | .003 | .01 | -.04 | .07 |
| Growth total compensation of employees | .02 | .02 | -.04 | .12 |
| Growth number of patent applications | -.05 | .16 | -.65 | .91 |
| Objective 1 | .33 | .47 | .00 | 1.00 |
| Eligible for Objective 1 | .32 | .47 | .00 | 1.00 |
| GDP per capita minus 75% of EU avg. | 3165.09 | 6611.39 | -8851.53 | 40895.61 |

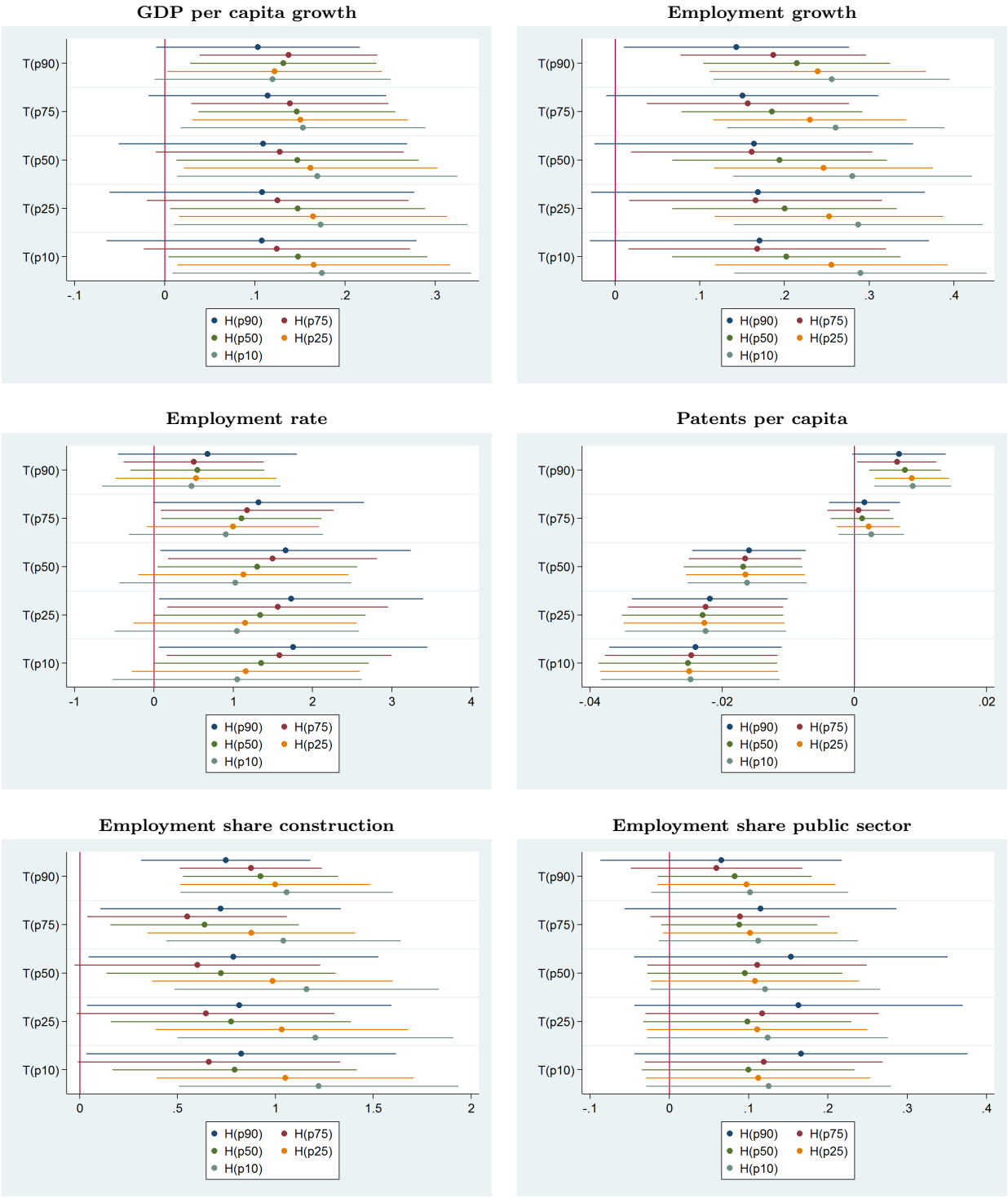
*Notes*: ..

Table A3: Descriptives NUTS3 – 2000-2013

| | Mean | StdDev | Min | Max |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Outcomes:** | | | | |
| GDP per capita growth | .01 | .02 | -.07 | .12 |
| Employment growth | .003 | .02 | -.07 | .09 |
| Prog. period avg. of annual patents per capita | .0003 | .0006 | .00 | .02 |
| Employment/active population | .89 | .18 | .40 | 2.37 |
| Growth in public sector employment | .009 | .02 | -.14 | .24 |
| Growth in construction employment | -.003 | .05 | -.25 | .35 |
| **Control variables:** | | | | |
| Log initial per capita GDP | 9.87 | .42 | 8.21 | 11.97 |
| Log initial population | 12.40 | .88 | 9.00 | 15.47 |
| Industry employment share (initial) | .20 | .09 | .02 | .59 |
| Public employment share (initial) | .29 | .07 | .07 | .52 |
| Agricultural employment share (initial) | .08 | .10 | .0001 | .65 |
| Service employment share (initial) | .26 | .05 | .09 | .61 |
| Financial service employment share (initial) | .10 | .04 | .01 | .39 |
| Construction employment share (initial) | .08 | .03 | .007 | .22 |
| Industry gva share (initial) | .23 | .10 | .002 | .74 |
| Public gva share (initial) | .23 | .07 | .03 | .57 |
| Agricultural gva share (initial) | .03 | .04 | 1.55e-07 | .29 |
| Service gva share (initial) | .22 | .06 | .05 | .57 |
| Financial service gva share (initial) | .21 | .07 | .04 | .70 |
| Construction gva t share (initial) | .07 | .03 | .008 | .25 |
| Employment/population (initial) | .43 | .10 | .21 | 1.13 |
| Log population density (initial) | 14.04 | 1.32 | 9.09 | 18.95 |

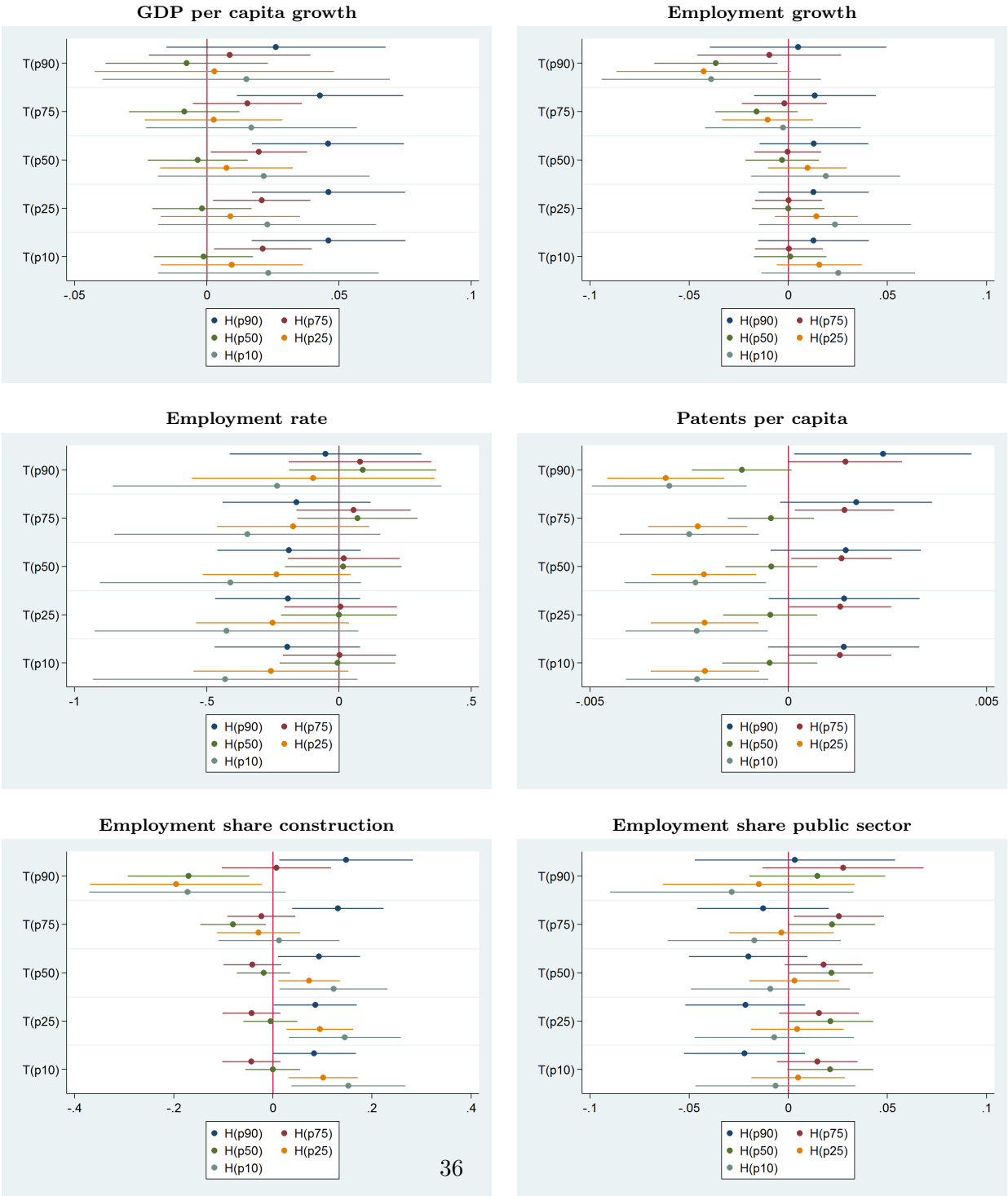
*Notes*: The estimation of the GPS includes all control variables, as well as their interactions and higher order polynomials. In addition we add country dummies, period dummies, and a dummy for the 'New Länder' in Germany.

Figure A1: Marginal effect of increase in transfer intensity $T$ holding transfer concentration $H$ constant (9 Groups)




*Notes*: The vertical layers in each graph refer to the percentiles $10, 25, 50, 75, 90$ of transfer intensity ($T$). The colors refer to the corresponding percentiles of transfer concentration across the 12 expenditure categories $H$. We measure the marginal effects on all outcomes in percentage points. To compute these marginal effects we raise transfer intensity (avg. annual transfers per initial gdp) by one percentage point. The dots illustrate the point estimates and the bars display the corresponding 90 percent confidence intervals. We base the sample on observations that satisfy the common support criterion based on 9 groups.

Figure A2: Marginal effect of increase in transfer concentration $H$ holding transfer intensity $T$ constant (9 Groups)




*Notes*: The vertical layers in each graph refer to the percentiles $10, 25, 50, 75, 90$ of transfer intensity ($T$). The colors refer to the corresponding percentiles of transfer concentration across the 12 expenditure categories $H$. We measure the marginal effects on all outcomes in percentage points. To compute these marginal effects we raise Herfindahl index by 0.01 times the standard deviation of the samples Herfindahl index. The dots illustrate the point estimates and the bars display the corresponding 90 percent confidence intervals. We base the sample on observations that satisfy the common support criterion based on 9 groups.