Short-term Effects of EU Regional Policy on Employment and GDP Growth in the 2014-2020 Budgetary Cycle

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Abstract

The aim of this paper is to uncover early effects of EU regional policy on employment and GDP growth in the 2014-2020 budgetary cycle. EU regional policy distributes funds based on regions GDP per capita being below or above a certain threshold. This paper exploits two of these thresholds to uncover effects of EU regional policy with a Regression Discontinuity design. The estimated effect of the status of less developed region on average annual growth in the employment rate and GDP per capita (in PPS) is 1.4% and 2.1% respectively. No effects were found of the status of transition region on either growth in the employment rate or GDP.

1 Introduction

Every six years EU member states negotiate a budget for the European Structural and Investment Funds (ESIF) for the coming budgetary cycle. The funds aim at reducing disparities in growth and employment among regions.[1] Less developed regions receive more funding so they can catch up with more developed regions in order to foster socio-economic convergence. Regional financial support makes up nearly a third of the EU overall budget and could therefore not be dismissed as insignificant. However, evidence on the effectiveness of these funds is relatively mixed in findings. It is thus no surprise these funds are not free from debate and public opinion often calls for budget cuts.

A recent report of the European Court of Auditors is likely to stir up the debate for the coming budgetary cycle (2021-2027). In the 2017 annual reports of the European Court of Auditors (ECA, 2018) it was feared it would become increasingly difficult for Member States to spend all available funds from the ESIF. Although difficult eligibility criteria for projects could be the reason why not all resources are used, critics would likely argue that having too much resources is a sign that too much money is spend. The Dutch member of the Court of Audit, Alex Brenninkmeijer, believes the argument of excess money is going to play a role in the coming negotiations in which Finland, The Netherlands and Austria already aim at reducing the budget available for Structural funds (Volkskrant, 2018).

It is likely that effectiveness of ESIF funding is going to be a part of the debate. Numerous studies have tried to assess the effectiveness of structural funds for previous budgetary cycles, with different results.[2] The effectiveness of funds during the current budgetary cycle is interesting in particular because of the revision of categories of regional statuses. In previous budgetary cycles there are only two categories: one of which is less developed regions, with a GDP per capita below 75% of the EU average; and developed regions, with a GDP per capita above 75% of the EU average. More funding is allocated to less developed regions. For the current budgetary cycle of 2014-2020 a new category of transition regions was added. Transition regions are regions with a GDP per capita between 75% and 90% of the EU average.

It is questionable if the addition of a new category is effective and the newly introduced category could be subject for debate. In a preliminary proposal for the new budgetary cycle of 2021-2027 the Eurpean Commission (EC) already proposed to keep the status of transition regions but raised the 90% threshold for transition regions to 100% (EC, 2018b). More regions are going to be classified as a transition region while the effectiveness of the third category has not been proven to be effective yet.

This study looks at the effect of being assigned either the status of less developed (below 75%) or transition (between 75 - 90%) region on employment

[1]See: the introduction of COM(2017) 755, Strategic report 2017 on the implementation of the ESIF.

[2]See for example a literature overview by Mohl and Hagen (2010) or a more recent literature overview in this paper.

and growth outcomes for the period 2014-2020. Employment is measured as the employment rate, the share of active people with work. Growth is measured as the growth in the regional Gross Domestic Product in purchasing power parities (GDP in PPS). Less developed and transition regions receive more funding and should therefore experience a larger growth in the employment rate and GDP. This study answers the following research question:

What is the effect of being qualified as a less developed or transition region on growth in the employment rate and GDP for the current budgetary cycle up to 2018?

This in turn could answer whether the difference between less developed, more developed and transition regions works. If there is no effect of being assigned the status of a transition region, the ESF and ERDF funds could still be effective. However, it could then be argued that the differential spending is not effective and resources are better spend somewhere else. The study is innovative in the sense that it studies a fairly recent and contemporary budgetary cycle where most studies are ex-post evaluations. On the one hand, ex-post valuations are preferable because they are able to consider the budgetary period as a whole. On the other hand, the results of ex-post valuations are often only available after the start of the next budgetary cycle. Policy makers therefore have to look at the previous cycle rather than the contemporary cycle when drafting up the future cycle. As a consequence, the EC looks at the period of 2007-2013 when drafting up plans for the period of 2021-2017, a difference of seven years.

The aforementioned question is answered with a regression discontinuity design (RDD) that exploits the threshold of 90% and 75% GDP per capita below which regions are eligible for the status of transition or less developed region. In a RDD, regions just below and just above the threshold are compared as these are likely to be similar on relevant characteristics. This research finds an effect of being assigned the status of less developed region on growth in the employment rate and GDP of 1.4 and 2.1% respectively. No effects of the status of transition region are found.

The outline of this study is as follows: in *section 2*, the theoretical framework of convergence economics is explained. In *section 3*, the state of the empirical literature on the effects of ESIF on employment and growth is reviewed. The framework of ESIF funding is explained in *section 4*. The study continues with the methodology (*section 5*) and a description of the data (*section 6*) in order to discuss the possibility of a RDD. In *section 7*, the estimation results are presented and in *section 8* the results of sensitivity and robustness checks. There is a discussion of results in *section 9*. The study finishes in *section 10* with a conclusion and recommendations for policy-making and further research.

2 Convergence in theory

The objective of the ESIF for the period 2014-2020 is to support the investment in jobs and GDP growth in all European regions.[3] Growth in GDP and jobs in turn should reduce economic and social disparities between regions. In that way, regions in the EU converge economically and form a more coherent economic area as a whole. Hence, ESI funds form an integrated part of the EU's cohesion policy. The idea behind funding is that substantial investments are needed for less developed regions to catch up to more developed regions and that their economies are underdeveloped partly because there are not enough resources for investment in these areas. ESI funds supply such resources. This rationale is closely related to the convergence hypothesis.

The convergence hypothesis is developed on the basis of the neoclassical economic growth model of Solow (1956). According to this growth model, all economies, independent of their initial development, will eventually end up in the same steady-state and thus converge. In the steady-state, economies have similar growth rates and are equally well developed. Barro et al. (2003) explain that the source of convergence in this model is the assumption of diminishing returns to capital. Less developed economies have a lower capital to labour ratio and their marginal product of capital is higher. For this reason, economies that lag behind and are not in this steady-state can achieve higher growth rates and catch up (Barro et al., 2003). But there are limitations to this theory. The theory assumes capital and technology can freely flow from one country to another and capital is inexpensive to come by. In practice, not all national or regional economies have sufficient government funds available or can attract capital to invest. It is for this reason institutions such as the world bank supply financial aid to developing countries and the EU regional policy supplies investments to less developed regions.

The view that all economies reach the same steady state is furthermore not mirrored by the real world. In reality it seems unlikely that all economies, whether looking at regions or countries, reach the same steady-state and equal levels of GDP per capita and GDP growth. For this reason, others argued there exists something as conditional convergence (Mankiw et al., 1992). Conditional convergence means countries reach the same steady states conditionally on having identical structural characteristics, such as educational attainment of the population or openness to trade. If countries differ in structural characteristics they will reach a different steady-state, but still have a higher marginal product of capital (and initially a lower capital-labour ratio) before reaching the steady-state (Mankiw et al., 1992). The conditional convergence hypothesis similarly implies, just as the regular or absolute convergence hypothesis, that economies not having reached their steady-state can achieve faster growth rates if sufficient investment is supplied. Although according to the conditional convergence hypothesis, economies with different structural characteristics reach different steady-states, it is still possible that all economies reach the same

[3] Article 90(1), EU regulation 1303/2013 laying down common provision on the ERDF, ESF, CF, EAFRD and EMFF.

steady state if all structural characteristics of economies are the same. It is therefore possible to create equally rich and equally fast growing economies by altering the structural characteristics of economies such that they're all the same. This is the rationale behind development policies that aim at intervening in structural determinants of an economy and also behind the regional policy of the EU.

What is important is that both hypotheses expect less developed economies to be able to reach higher growth rates and in turn converge by increasing capital and because their marginal product of capital is higher. The European Structural and Investment funds try to achieve exactly that by supplying investments. Furthermore, based on the conditional convergence hypothesis, for countries to truly convergence they need to achieve similar structural characteristics. The name is no coincidence as the ESI try to invest in the structural characteristics of regional economies in order for them to achieves structurally higher growth paths.

Because of the convergence hypothesis, it is expected that less developed regions in the EU have higher growth-rates regardless of any policy instrument because economies grow faster the further away they are from the steady-state. For this reason it is expected that growth rates are increasingly higher the less developed a region is. The European Structural Investment Funds stimulate regional development and growth rates by providing resources for investment, and by aiming investments at altering the structural characteristics such that less developed regions catch-up. In light of this we expect growth rates for regions receiving funding to be even a little higher than of those that do not receive funding.

It is difficult to distinguish the policy effects of the ESI on growth-rates from less developed regions having higher growth-rates naturally because they are not in a steady-state yet. If one would compare rich and poor economies and the poorer economies have higher growth rates and receive funding one could falsely conclude this is because of funding from the ESI. Theory suggest however that poor economies have higher growth rates because they are further away from reaching a steady state. Distinguishing the effects of ESI on growth rates from the convergence hypohtesis effects on growth rates could potentially be done by an RD-design. To be able to employ such a RD-design a thorough knowledge of the policy and its assignment rules is needed. The next paragraph discusses how previous studies assessed the effects of ESI funding on growth in the employment rate or GDP. Thereafter the paper provides an insight in the ESI policies for the current budgetary cycle.

3 Empirical literature review

The idea that regional redistribution could contribute to (economic) cohesion goes way back and lies at the heart of the European Community. Because a large part of the EU-budget is concerned with redistributing funds, the effectivity of transfers has always been important. Since the 2000s a lot of quantitative research has been done to the effectiveness of structural funds. Most studies differ greatly in the budgetary cycle or geographical area of interest, the research method applied and even in findings. This section discusses relevant findings of effect studies looking at the effect of European Structural and Investment Funds (ESIF). Because studies differ so much in region or budgetary period of interest, table 1 gives an overview of the characteristics of discussed literature.

Several cross-sectional studies find limited or no effects of Structural funds on growth or employment outcomes. Eggert et al. (2007) find for Germany that the EU's regional transfers reduce average growth rates. They argue there is a trade off between regional growth and average growth and regional policies potentially limit efficient factor migration and in turn average economic growth. De Freitas et al. (2003) use a larger set of regions where they control for national institutions. They find less developed regions that receive more funding do not show faster convergence because of extra funding. They argue convergence is more likely to be caused by differences in quality of national and regional governance, thereby questioning the effectiveness for differential funding between regions.

Another cross-sectional study by Dall'erba (2005) finds a positive relationship between structural funds and regional growth by taking into account spatial dependencies of regions. Spatial dependencies could be important when regions surrounding a supported region benefit from funding because of spill-over effects. In a later collaboration with Le Gallo, Dall'erba and Le Gallo (2007) consider the same sample as in the study mentioned before but introduce a different spatial model and differentiate between different objectives of funding. They find no effect of structural funds on regional convergence or employment. The different results from those two studies indicate that spatial dependencies could play an important role in assessing effects and that effects could depend on the method used. When using regional observations to study convergence and growth it could therefore be important to keep spatial autocorrelation in mind (See also: Abreu et al., 2004; Arbia et al, 2008; Anselin et al. 2013).

Aforementioned studies are based on cross-sectional analysis, with observations of different subjects at only one point in time. Mohl and Hagen (2010) argue that the use of panel data, with observations over time for different subjects is preferable as there is more variation and less collinearity in the data. They look at the effect of actual payments for different objectives of EU Cohesion Policy and find positive effects of transfers to less developed regions on economic growth but not on employment. Mohl and Hagen argue positive effects are observed because the payments to less developed regions are based on clear criteria and lead to economically efficient investment projects. Their study is later extended to allow for conditionality, a situation where structural funds are effective conditional on a region having certain structural characteristics.

Indeed, various panel studies find that structural funds are only conditionally effective and there is an effect only for specific groups, regions or people. In a panel study to Portuguese regions, ESIF were effective only for coastal regions because coastal regions are located more favourably (Soukiazis and Antunes, 2006). Others find that structural funds are only effective when directed at human capital because other transfers tend to function as income support rather than improving labour productivity (Rodriguez-Pose and Fratesi, 2004). Mohl and Hagen (2011) extended their previously mentioned research with effects conditional on the skill level of the population and find that structural Funds are only effective in enhancing employment for regions with a high-skilled population. Additionally, in a meta-study to 17 econometric studies looking at effects of structural funds, Dall'Erba & Fang (2017) find that significant differences in effects between studies are caused by the inclusion of different endogenous regressors. They find it matters a great deal for estimated effects whether a study takes into account measures for human capital, or investments in education. Previous findings thus show the importance of considering human capital when assessing the effects of structural funds on either growth or employment.

The use of panel-data estimation techniques for investigating the effects of ESIF payments is however limited for its own reasons. First, regions are highly heterogeneous. It is unlikely that all heterogeneity could be captured by observed covariates used in panel-data approaches. Second, regionalized datasets of the European Commission's regional policy branch (DG-Regio) on historical payments that have data for all regions are often of limited reliability (EC, 2017). In the construction of these EU-wide data sets researchers have to cope with different systems between nations or lacking or delayed data on distributions among regions. To construct big data sets statisticians sometimes use assignment rules to fill up gaps in the data and distribute known payments on the national level to regions (Roemisch, 2016; EC, 2017). An assignment rule for missing regional data on ERDF payments could be regional population shares while an assignment rule for ESF funding could be a weighted regional share of unemployment in a country. As a consequence, structural funds expenditure data does not always deviate from relevant economic indicators such as the employment rate. This does not necessarily invalidate all panel-data approaches, in the end it depends on the data set and accompanying research question for a method and data set to be valid.

Because this research looks at the effect of structural funds on growth and employment it is better not to use payment data that does not deviate from employment indicators. This could in fact be a reason why aforementioned panel data approaches did sometimes not find any effects of structural funds on employment outcomes. There is a way to circumvent problems with data on expenditures by using eligibility criteria. In spite of data gaps in expenditure data it could still be assumed that national and regional authorities distributed and received funds on the basis of strict eligibility criteria. It could simply be a too daunting task to construct ex-post EU-wide regional data sets on actual expenditure data.

Several studies use eligibility criteria rather than expenditure data to assess the effects of structural funds, often by means of a regression discontinuity design (RDD). In a RDD, a treatment and control group are created just above and below a certain threshold that determines treatment. This creates a quasi-experimental research design. An advantage of an RDD over a panel data approach is that the assumption of randomization is more plausible and there is less need to control for unobserved characteristics. Becker et al. (2010) study the causal effect of being assigned the status of less developed region on employment and GDP growth with a RDD. They find positive and significant effects for GDP per capita growth but no significant positive effects for employment growth. Becker et al. control in in their research design for spatial correlation. In theory, spatial auto-correlation is less of a problem in a RDD because regions just below and above the threshold (in the treatment and control group), are equally likely to be close to other regions that are treated. However, Becker et al. try to control for spill-over effects by including dummies for the proximity of a treated region. Their results appear robust for spatial correlation between regions. This could be an indication that spatial dependence is indeed less important in an RDD.

Pellegrini et al. (2013) similarly studied the effect of regional transfers to less developed regions on growth outcomes by using a RDD. They find positive effects on GDP growth but no effects on employment as well. Their analysis however excludes regions that switched treatment between budgetary cycles. The omission of these regions probably interferes with the control and treatment groups as these regions are likely to be close to the cut-off.

Becker and Pellegrini both extend their studies in later collaborations. Becker shows there exist heterogeneous treatment effects of transfers to less developed regions (Becker et al. 2013). Positive effects of structural funds transfers on GDP growth only exist for regions with high human capital and well developed institutions, stressing again the importance of education when looking at the effects of structural funds. Their results reinforce aforementioned findings of Mohl and Hagen (2011) showing there are effects only conditional on a high-skilled population. Pellegrini extends the RD-design to investigate whether too much is spend on Structural funds by evaluating the intensity of treatment (Cerqua & Pellegrini, 2018). They estimate an intensity-growth function and find that more funds do not necessarily lead to more growth. It is therefore argued that too much is spend and more efficiency could be achieved by reallocating funds.

Besides the sensitivity of effects to certain conditions imposed on the group of interest, the timing is important. In the previously discussed paper of Becker et al. (2010) it was found that significant effects appear after three years only and become stronger. This implies we would not capture the full effect when studying a current budgetary cycle (that is only four years underway). Interestingly enough, these findings are contradicted by a later study of the same author. When studying a larger sample (1989-2013), even immediate effects are found by Becker et al. (2018). Their recent research shows that growth effects could be undone when regions lose eligibility status. So even though the effect of transfers are not long-lived, immediate effects on employment are visible when regions gain eligibility to receive funding.

It follows from the previous discussion that there is no clear-cut answer on the effectiveness of ESIF on growth in GDP or employment although more recent literature seems to point at positive effects under certain conditions. Important conditions are regional institutions and human capital. It is expected that effects are stronger for regions with more human capital and a more developed institutional framework. Besides conditionality, any research to the effects of Structural funds should consider spatial dependence and the reliability of regional expenditure data.

Table 1: Overview of empirical literature

Author (year)	Method	Sample size (period)	Findings
Eggert et al. (2007)	Cross-sectional	16 NUTS 1 in Germany (1989-1993)	Regional transfers reduce average growth rates
De Freitas et al. (2003)	Cross-sectional	196 NUTS 2 (1990-2001)	No convergence (less-developed regions do not catch-up)
Dall'erba (2005)	Cross-sectional with spatial dependencies	145 NUTS 2 (1989-1999)	Positive effect of strucutural fund transfers on economic growth
Dall'erba and Le Gallo (2007)	Cross-sectional spatial lag	145 NUTS 2 (1989-1999)	No effect of structural funds on economic growth or employment growth
Mohl and Hagen (2010)	Panel data	130 NUTS 2 (2000-2006)	Positive effect of actual payments on economic growth
Soukiazis and Antunes (2006)	Panel data	30 NUTS 3 in Portugal (1991-2000)	Structural funds only effective for non-interior regions
Rodriguez-Pose et al. (2004)	Cross sectional and panel data	152 NUTS 2 (1989-1999)	Structural funds only effective conditional on high human capital
Mohl and Hagen (2011)	Dynamic spatial panel data approach	130 NUTS 2 (1999-2007)	Structural funds only effective for regions with a high-skilled population
Dall'Erba and Fang (2017)	Metastudy to 17 econometric studies	n/a	Human capital, investments in education or institutional quality are important
Becker et al. (2010)	Regression-discontinuity	193-295 NUTS 2 (1989-2006)	Positive effects of structural funds on growth but not on employment
Pellegrini et al. (2013)	Regression-discontinuity	213 NUTS 2 (1994-2006)	Positive effects on growth but not on employment
Becker et al. (2013)	Regression-discontinuity	186-251 NUTS 2 (1989-2006)	Positive effects of structural funds on growth only conditional on high human capital
Cerqua and Pellegrini (2018)	Regression-discontinuity	208 NUTS 2 (1994-2006)	Intensity of funding does not matter
Becker et al. (2018)	Regression-discontinuity	187-253 NUTS 2 (1989-2013)	There exist immediate effects of structural funds

4 The framework of EU funding

The European Structural and Investment Funds (ESIF) make up around 500 billion euros of the budget for the cycle of 2014-2020 (EC, 2017a). Out of the five ESIF, the European Regional Development Fund (ERDF), the European Social Fund (ESF) and the Cohesion fund (CF) are the largest funds for which the most financial resources are available. These three funds are distributed on the basis of economic indicators. The ERDF and ESF are regionally distributed on the basis of regional GDP per capita in purchasing power standards (PPS). The CF is distributed to countries with a low Gross National Inocme (GNI).

As mentioned before, the objective of the structural Funds for the period 2014-2020 is to support the investment in GDP and employment growth in all NUTS level 2 regions. The NUTS classification is a single system in which the territory of the European Union is divided into territories on different levels of roughly equal population size in order to produce statistics. NUTS level 2 regions have a minimum population of 800.000 and a maximum of 3 million and are therefore of roughly the same size.[4] During the current cycle of 2014-2020, financial resources for the ERDF and ESF are allocated among three categories of regions divided by their relative GDP per capita. Less developed regions have a GDP per capita of less than 75% of the EU average, transition regions have a GDP per capita between 75% and 90% of the EU average while developed regions have a GDP per capita above 90% of the EU average.[5]

For the purpose of classifying regions in the latest budgetary cycle, GDP per capita (in PPS) is measured as the average of 2007-2009, well before the start of the current budgetary cycle.[6] The use of PPS allows for meaningful comparisons between regions as this measure eliminates differences in price levels. The average GDP per capita of all 28 EU member states is set to 100. The GDP per capita in PPS criterion is the eligibility for treatment which is also called the *assignment rule* or rating variable in this research. A region should be treated as transition or less developed region if it falls below either the 90% or 75% threshold. In reality however, data on regional GDP per capita is delivered too late for a couple regions. The final decision on the actual *treatment* of regions as transition or less developed regions might therefore differ slightly from the division that would be made solely on the basis of eligibility. Actual treatment is laid down in decisions of the European Commission. In the data section it is explored whether eligible regions are also treated regions or not. This only deviates in a few cases. If some regions are treated while not being eligible according to the assignment rule or vice verse the suitable regression discontinuity design would be a fuzzy regression discontinuity design. This is checked and explained in the data section of this paper.

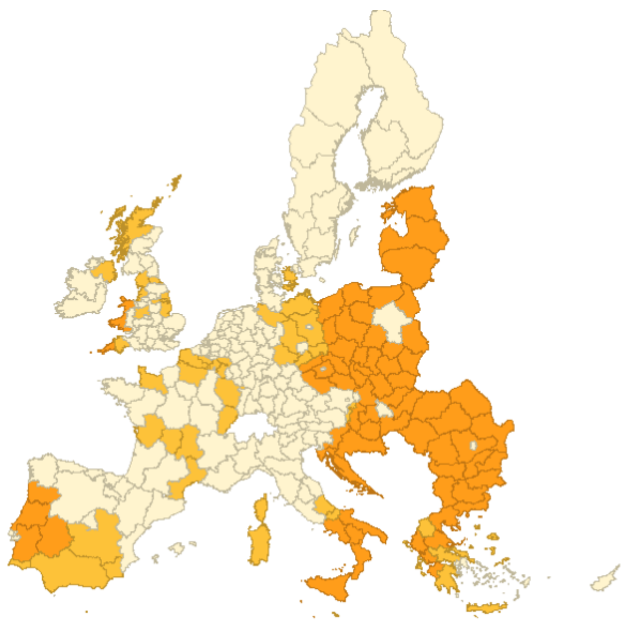
[4]Article 3(2), EC regulation 1059/2003, on the establishment of a common classification of territorial units for statistics

[5]Article 90(2)(a)(b)(c), EU regulation 1303/2013 laying down common provision on the ERDF, ESF, CF, EAFRD and EMFF.

[6]Article 90(2)(a)(b)(c), EU regulation 1303/2013 laying down common provision on the ERDF, ESF, CF, EAFRD and EMFF.

Figure 1 shows the location of treated regions in the European Union. The lightest regions are classified as developed regions, light-dark regions as transition regions while the darkest regions are less developed regions that receive the most funding. For the purpose of this study we exploit the threshold of 90 and 75% making a division between transition and developed regions and less developed and transition regions. Although the co-financing rates between transition and development regions do not differ a lot (structural funds can cover 50% of the financing of a project in developed region and 60 % in a transition region), the total amount of available resources does. For a total of 51 transition regions 32billion euros are available while for a total of 151 developed regions 49 billion euros are. A simple calculation would show that per region almost double the amount of resources is available for transition regions.

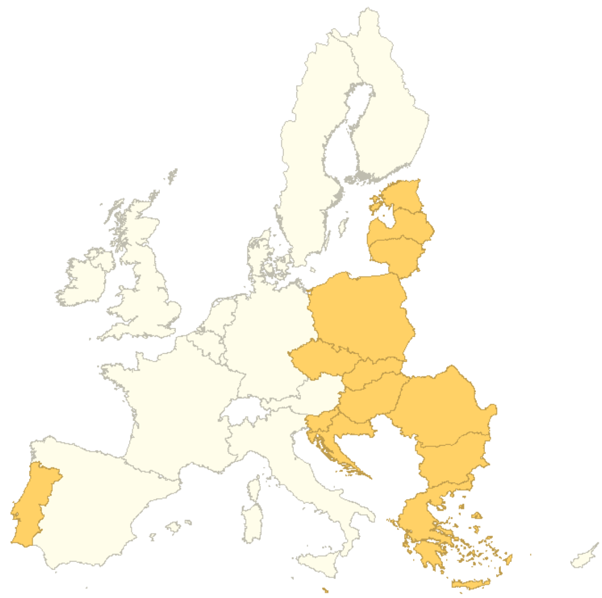
Figure 1: Regional status for ESF and ERDF funding per NUTS 2 region



Note: NUTS level 2 regions are colour-coded by their regional status. Regions with a developed status have a GDP per capita (in PPS) above 90% of the EU average and are light colored. Regions with a transition status have a GDP per capita between 75% and 90% and are coloured darker. Regions with a less developed status have a GDP per capita below 75% and are coloured darkest.

A concern for any estimation at the threshold are spillovers of other programs that use the same threshold. A potential candidate that could contaminate the regression discontinuity design is the Cohesion Fund (CF). The CF is allocated on the Member-state level and supports member states with a GNI per capita below 90%. Figure 2 shows countries that are treated under the CF.

Figure 2: Cohesion Fund eligiblity per country



Note: Countries that are eligible to receive funding from the Cohesion fund have a GNI below 90% of the EU-average and are coloured darker.

From figure 1 and 2 is visible that most transition and developed regions are located in countries that do not receive funding from CF. Contamination of the CF is therefore unlikely when considering division between transition and developed regions and a little more likely when considering the division between less developed and transition regions, but could be controlled for in any analysis because it is known. It should however be noted that the budget for the CF (75 billion euro) is much lower than that of the ESF and ERDF combined (around 400 billion euro).

Another geographical feature of ESIF funding is that most transition and developed regions are located in the same member states. Figure 1 shows that France, Germany, the United Kingdom, Spain and Italy have both transition regions and developed regions. This makes it even more likely that untreated and treated regions are similar on all other dimensions except for the fact they are on either side of the 90% cutoff. Regions within countries share a similar institutional set-up and political or cultural environment. Countries with only developed regions are more likely to be far away from any RDD threshold. The differences between regions with different regional statuses are further explored in the data section of this paper. First the methodology of the RD design is described in the next section.

5 Methodology

This research estimates the effect of the status of a transition or less developed region (hereafter to be called treatment status) on growth and employment in the budgetary cycle of 2014-2020 by means of a regression discontinuity design. The main assumption behind a regression discontinuity design is that subjects just below or just above a cutoff point of treatment are similar and could therefore be used as a control and treatment group. The only difference being whether a region is treated or not. Regions with the status of transition region or less developed region are 'treated' with extra funding while regions with a status of a developed region are not. Regions are formally eligible for treatment with extra funding if their GDP per capita is below 90% (transition region) or 75% (less developed region) of the EU average. A region with a GDP per capita of 90.01% of the EU average is therefore untreated while a region with 89.99% is treated. These regions are likely to be comparable although they differ in treatment. The 90% and 75% assignment rules therefore essentially create two comparable groups of regions.

If there is a strong effect of treatment with extra funding from structural funds, it is expected that growth in employment or GDP is higher for the treated regions just below the cutoff. This appears in the data as a sudden jump in the outcome variable just below the cutoff when we plot the outcome variable (e.g. GDP growth) against the assignment variable (GDP per capita relative to the EU average). This is checked in figure 4a to 4d in the data section of this paper.

Two issues could potentially invalidate the RD-design: (i) manipulation of treatment and (ii) discontinuities in other covariates.

(i) The first arises when subjects have control over the assignment of treatment. There is a possibility that regional or national authorities have control over regional statistics and are capable of manipulating the data such that they receive a beneficial regional status with a corresponding high level of funding. In that case there is interference with the control and treatment group and the groups are unlikely to be comparable.

(ii) The second issue that could potentially invalidate an RD-design is a discontinuity in any other variable that could influence the outcome variables. If for example the share of tertiary educated people causes higher GDP growth rates, and the share of tertiary educated people is not continuous over the rating variable (GDP per capita) but shows a jump at the cutoff point, there is a jump in the outcome variable as well. It is then not possible to estimate the effect of ESI funds on GDP growth rates as this could be caused by either extra funding with or a discontinuous jump in the share of tertiary educated people. In the data section it is verified whether these two issues could potentially invalidate the regression discontinuity approach or not.

The effect of treatment on growth in the employment rate and GDP is then estimated by using the regression model depicted in equation 1, the baseline equation of this research. In equation 1, $Growth_i$ denotes the average annual growth in GDP per capita or the employment rate between 2014 and 2018 for region i. α_i is a constant. $GDP09_i$ is the assignment variable, GDP per capita (in PPS) relative to the EU average in the period 2007-2009. This variable is captured by a functional form $f()$. $Treat_i$ indicates whether a region is assigned treatment status or not (meaning that a regions is assigned the status of less developed region below the 75% threshold or transition region below the 90% but above the 75% threshold). The variable is a dummy equaling 1 if region i is assigned treatment status and zero otherwise. Denoted by ρ is then the estimated jump in the outcome variable at the threshold which is the effect of treatment status on average annual growth in GDP or the employment rate.

$$Growth_i = \alpha_i + \rho Treat_i + f(GDP09_i) + \epsilon_i \tag{1}$$

If formal eligibility of treatment by either the 75% or 90% rule is not strictly adhered to, some regions are assigned the status of less developed or transition region and therefore receive treatment while their GDP per capita was above 75% or 90% in the period 2007-2009. These regions are called non-compliant regions because they do not comply to the assignment rule. Formally these regions were not eligible and should not have been treated. If one would estimate equation 1 the estimates are likely to be biased (Lee and Lemieux, 2009). This problem can be overcome by using an instrumental variable approach for treatment. In equation 2 actual treatment status ($Treat_i$) is instrumented on the formal eligibility rule where $Rule_i$ indicates that a country is eligible for treatment according to the assignment rule of 75% or 90% of GDP per capita relative to the EU average for the status of less developed and transition region respectively. This procedure works as long as the probability of receiving treatment is different for regions above and below the cutoff. Equation 2 presents the first-stage regression in which $Treat_i$ is instrumented on the eligibility rule $Rule_i$.

$$Treat_i = b_i + \beta Rule_i + f(GDP09_i) + u_i \tag{2}$$

The estimated values of $Treat_i$ in the first stage regression equation 2 could be inserted into equation 1 to get unbiased estimates of ρ. It is important to use the same specification in the first-stage as in the second stage. Three other aspects should be considered in estimating baseline equation 1; (i) the bandwidth for the estimation, (ii) the functional form $f()$ and (iii) the kernel used.

(i) The bandwidth of the estimation specifies the range of observations above and below the cutoff to be taken into account for the estimation of equation 1. If all regions are used for the estimation, there is more variation in the data and estimates are more precise. However, the probability that control and treatment group differ from each other on important characteristics is large. There is thus more bias in the estimates. If only regions with a GDP per capita between a small bandwidth are used, say between 85% and 95% of the EU average, there is likely to be less bias but estimates of ρ are less precise. There is thus a trade-off between bias and precision. For this research the optimal bandwidth with the lowest Mean-Squared Error is calculated by using a data-driven cross-validation criterion (Ludwig & Miller 2007; Lee & Lemieux 2009).

Because the data-driven approach in this particular research results in a low number of observations a bandwidth of 10 percentage points on both sides of the cutoff is used for the baseline estimation. As a robustness check equation 1 is estimated on two more bandwidths of 5 and 15 percentage points below and above the cutoff.

(ii) The second aspect is the functional form $f()$ with which the assignment variable is captured. It is advisable to use a polynomial of a small order because higher order polynomials might invalidate results. Results for causal effects based on high-order polynomials are sensitive to the order of the polynomial. Next to this, high-order polynomials tend to attach too much weight to outliers in the assignment variable (Gelman & Imbens, 2018). For this research the linear functional form is therefore used in the baseline. Equation 1 is additionally estimated with a quadratic and cubic functional form $f()$ to be able to say something about the robustness of the results.

(iii) The third aspect is the choice for a kernel. A kernel is a weighting function that attaches weight to observations used in estimating equation 1. A uniform kernel attaches equal weight to every observation independent of its distance to the cutoff. An epanechnikov and triangular kernel attach more weight to observations close to the cutoff and less to observations far away. Empirical studies often favour the triangular kernel because in a RD-design the researcher is interested in the difference at the cutoff. It therefore makes sense to attach more weight to those observations. Equation 1 is estimated with the other two kernels as a robustness check.

The effect of treatment status on growth in GDP and the employment rate is correctly estimated when using the right bandwidth, kernel and a proper functional form. The baseline estimation of this research is the estimation with a bandwidth of 10 percentage point on both sides of the cutoff, a triangular kernel and a linear functional form. If the RD-design is then not invalidated by either (i) manipulations of the assignment variable or (ii) discontinuities in other baseline covariates the RD-design is internally valid but not necessarily externally valid. Meaning that the estimated effect is informative of the effect on regions in proximity of the cutoff but not of regions with a GDP per capita relative to the EU average far away from the cutoff, say 30% for example, because these are not considered in the estimation.

Furthermore, when using equation 2 to estimate a fuzzy design, the estimated effect is only a local average treatment effect (LATE). This implies that the effect is only the effect of receiving extra funding for regions that received extra funding while at the same time these regions were eligible according to the assignment rule to receive extra funding (Angrist & Pischke, 2009). The effect is not representative for the effect of receiving extra funding for always takers (regions that always receive funding whether eligible or not), never takers (regions that never receive funding whether eligible or not) and non-compliant regions (regions that do or don't receive funding opposite to their eligibility). External validity of any estimated effect is therefore low and could not easily be assumed. This however is also the case for a sharp RD. Any effect will therefore not be the effect of extra funding on regions with a GDP per capita of for example 30% or 120% of the EU average but rather of those regions with a GDP per capita close to either 75% or 90% of the EU average. In the section on robustness checks several other specifications of the baseline model in equation 1 are discussed. These alternative specifications are used to examine the robustness of the results while taking into account the other baseline covariates, spill-overs from the Cohesion Fund and the conditionality of effects on human capital.

Because historic EU-wide regional expenditure data from the Eu's department regional policy is sometimes constructed from employment indicators this research uses eligibility criteria rather than expenditure data (Roemisch, 2016; EC, 2017). When using expenditure data constructed with employment indicators, the expenditure data does not deviate from employment indicators and it is not possible to estimate an effect. Another reason for the use of eligibility criteria rather than expenditure data is the focus on a recent budgetary cycle. Regional reliable expenditure data is often delayed and only available after the end of the budgetary cycle. The objective of differential funding for the current cycle is to improve jobs and growth. For this reason, positive effects of treatment growth in the employment rate and GDP are expected. Effects are expected to be visible already because previous research found immediate effects and effects after three years already. In the next section, effects are examined visually in the data after the data is described and the internal validity of the RD-design is established.

6 Data

The data for this study is regional data collected by Eurostat, the statistical bureau of the European Union, trough national statistics bureaus.[7] Regional data is collected by Eurostat for the specific purpose of assessing the EU regional policy and making objective comparisons between regions possible. This research uses average annual growth in the regional GDP per capita (measured in PPS) and the employment rate as outcome variables. Other annual regional variables used are the median age of the total population, share of employed in industry, population density and the share of tertiary educated in the population aged 25-64. All data used is annual data. The research uses GDP per capita data from 2007 (the reference year for assigning treatment) to 2017 and other variables from 2013 (the year before the treatment period) to 2018.

In this section the statistical system for regions and changes therein are discussed first because these define the subjects of the research. A description of the data is given thereafter together with a visual inspection of discontinuities in outcome variables that could hint at treatment effects of ESI funding on employment and growth. The section finishes with discussing the internal validity of the RD-design.

6.1 Nomenclature of Territorial Units for Statistics (NUTS)

The Nomenclature of Territorial Units for Statistics (NUTS) is a system for defining regions for the purpose of statistics. There are several levels on which regions are defined (i.e. level 1 is on a macro-level while level 3 is often on a municipality level). This research uses data from NUTS level-2 regions because structural funds are distributed based on regional characteristics on this level. NUTS level-2 regions are therefore the subjects of this research. Level 2 regions have a minimum population size of 800.000 and a maximum of 3 million and are thus of roughly the same size.[8]

Naturally, population sizes change over time. NUTS classifications are therefore revised every three years. In case changes are made, historical data is replaced within two to three years according to the new regional breakdown of a region.[9] For this study changes in the NUTS level 2 classifications between 2010 and 2013 are important because data used is from the NUTS 2013 classification while EU decisions on regional treatment status were made using the 2010 classification. The 2016 classification is less important because these changes are only going to be reflected in the data in later years.

Between classifications regions could either be left untouched, recoded, split, merged or redefined by a boundary shift. If regions are recoded, regions are only renamed which does not obstruct any analysis. In the case of split or merged regions it is possible to simply work with new data because the

[7] Eurostat regional database: https://ec.europa.eu/eurostat/web/regions/data/database

[8] Article 3(2), EC regulation 1059/2003, on the establishment of a common classification of territorial units for statistics.

[9] See for all historic changes: https://ec.europa.eu/eurostat/web/nuts/history

newer data is calculated for historic time periods as well. More problematic is a boundary shift. In case of a boundary shift the geographical area of a region changes. The data is of course recalculated afterwards, but if the boundary shift changes an area from an untreated to a treated region this could bias results. All seventeen changes are discussed briefly of which only two could potentially bias results. An overview is given in the appendix in table A.1.

Between 2010 and 2013 regions in Greece got recoded. This is no problem for any analysis as regions do not change. In France, new overseas regions are added by splitting old regions. Overseas regions are excluded from the data as the focus of this research is on mainland Europe.[10] Both changes in Greece and France do therefore not obstruct the research. In the UK, the regions Inner and Outer London were split into respectively two and three new regions. No regions would have to change treatment eligibility after the split according to the GDP per capita eligibility rules except for UKI5 (Outer London – East and North East). The latter would need to classify as a transition region while it is in fact classified as a developed region. For this research the newly recalculated data for the split London regions is used where UKI5 is treated as non-complying subject. In Slovenia there was a small boundary shift between two regions. These are the only two regions that changed borders between classifications which could potentially change outcomes. The boundary shift however is small and will be ignored for the purpose of this research.[11]

After having established all the changes in regional subjects it is possible to look at the differences between eligible regions and treated regions. As explained before, there is a difference in eligibility of treatment status and actual assignment of treatment status. Regions are eligible for treatment if their GDP per capita in the period 2007 and 2009 is below 90% or 75% of the EU-average. Regions are assigned an actual treatment status if the formal EU decision on their regional status assigns them a treatment status. The formal decision that sets out the list of regions is the Commission implementing decision of the 18th of February 2014 (EC, 2014).

Table 2 shows the amount of regions eligible for treatment status based on the 2007-2009 GDP per capita (in PPS) rule and treatment based on the implementing decisions of the European Commission.

From table 2 is clear that the actual assignment rule (eligibility) is not strictly adhered to. Less regions are treated with a transition status than would solely be the case according to the assignment rule. A closer inspection reveals one Czech and Italian region receive less developed status while their GDP per capita is above 75% in the period 2007-2009 (ITF5 and CZ02). Two Greek regions are assigned the status of transition region while their GDP is too low (EL65 and EL41). Eight regions are assigned the status of developed regions while their GDP is lower than 90% (UKI5, UKF1, UKC2, PL12, UKG3, ES11, UKH3 and UKK2) and five regions are assigned the status of transition region

[10]Excluded overseas regions are Mayotte, French Guiana, Reunion, Guadeloupe, Martinique (FRA1 to FRA5), Melilla, Ceuta, The Canary Islands (ES63, ES64 and ES70), The Azores and Madeira (PT20 and PT30)

[11]See: https://ec.europa.eu/eurostat/documents/345175/7451602/nuts-map-SI.pdf

Table 2: Eligibility and Treatment

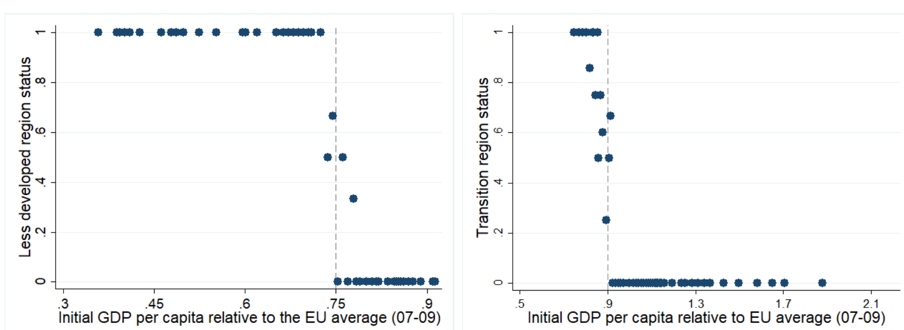
	Eligibility	Treatment
Less developed	66	66
Transition	50	47
More developed	148	151
Total	264	264

Note: Table 2 shows the number of regions by treatment status according to the eligibility rule based on GDP per capita relative to the EU average in the period of 2007 to 2009 and by actual treatment based on the formal decision setting out the regional status (EC, 2014).

while their GDP is in fact higher than 90% (ITF1, EL62, UKD1, UKM6 and UKE1). In total there are four non-compliant regions at the 75% cutoff and 13 at the 90% cutoff. The most important reason for non-compliance is that final correct data is provided too late in some regions for the European Commission to draw up the formal decision on treatment status. Compliance with the assignment rule is therefore not perfect and could pose a problem when estimating effects especially at the 90% cutoff. In Figure 3a and 3b non-compliance is inspected visually.

Figure 3a and 3b show assignment of less developed and transition region status plotted against the initial GDP per capita relative to the EU average between 2007 and 2009. Points represent equally sized bins and could contain multiple observations. The average treatment of a bin could therefore be between 0 and 1.

Figure 3: Compliance with the assignment rule



(a) Less developed status

(b) Transition status

Note: Figure 3a and 3b show average treatment status in equally sized bins. One bin can contain multiple observations. One observation is excluded from the figure; West Inner Londen (UKI3) had the status of developed region and a GDP per capita 5.6 times of the EU average. The observation is excluded to improve graph readability (but to be sure, UKI3 is assigned the status of a developed region).

Figure 3a and 3b show again that treatment status is not strictly implemented. Not all regions that should receive the treatment according to respectively the 75% or 90% eligibility rule are assigned the status of less developed or transition region. There are also regions that received treatment while they should not have. The assignment of regional status is therefore not perfectly sharp. This does not have to be a problem because the probability of treatment is different on both sides of the cutoff. The research design then only changes to become a fuzzy design. Besides, it is possible to exclude the non-complying regions to get a sharp-design again as it only concerns a few regions.

6.2 Description of data

With the regional subjects of the research discussed it is possible to turn to some descriptive statistics of the outcome variables. Estimating an effect of structural funds only makes sense if there are any differences in outcomes for different regions. Table 3 shows the growth of employment and GDP together with the situation before the start of the budgetary cycle 2014-2020 for all regions together and by treatment status (either less developed, transition or more developed). The mean initial GDP per capita relative to the EU average is not 1 but 0.98. This is because the mean is calculated without weighting regions based on their population whereas the average GDP per capita in the EU statistics is weighted. The mean furthermore is highest among developed regions and lowest among less developed regions (because it is the rating variable that determines regional status). Likewise, employment is lowest among less developed and highest among developed regions although disparities among regions are quite high. The highest employment among less developed regions is 70% (CZ02, Central Bohemian) which is higher than the mean employment of transition and developed regions. Similarly, the region with the lowest employment among developed regions has an employment level of only 49.2% (EL30, Metropolitan Athens) which is much lower than the mean of less developed regions. Disparities in employment levels are therefore high.

Table 3 furthermore shows average annual GDP per capita growth (in PPS) in 2014-2016. There is no difference in mean GDP growth between regions with a developed or transition status while mean GDP growth in less developed regions is considerably higher, although just within one standard deviation of the mean. The regions with highest (IE02, Southern and Eastern) and lowest GDP-growth (NL11, Groningen) are among the developed regions. The latter of which saw a dramatic decline in GDP after the EU's largest gasfield was shut.[12] No less developed regions experienced negative growth over the period 2014-2016.

The average annual growth in the employment rate for the period 2014-2017 is more different between regional statuses. For all groups except the group of less developed regions there are regions with negative and positive employment growth, the largest positive value is located in the less developed group of regions. Employment growth was on average 1% for developed regions, 1.4% for

[12] ec.europa.eu/growth/tools-databases/regional-innovation-monitor/base-profile/province-groningen

Table 3: Summary statistics of regional variables

All regions

Variable	Obs.	Mean	Std. Dev.	Min	Max
Initial GDP per capita relative to the EU average	264	0.980	0.450	0.277	5.633
GDP Growth*	264	0.027	0.018	-0.109	0.171
Employment 2013	264	64.891	8.651	38.9	78.7
Employment Growth*	264	0.014	0.011	-0.007	0.053

Developed regions

Variable	Obs.	Mean	Std. Dev.	Min	Max
Initial GDP per capita relative to the EU average	151	1.211	0.454	0.82	5.633
GDP Growth *	151	0.024	0.019	-0.109	0.171
Employment 2013	151	68.850	6.348	49.2	78.7
Employment Growth *	151	0.010	0.008	-0.004	0.035

Transition regions

Variable	Obs.	Mean	Std. Dev.	Min	Max
Initial GDP per capita relative to the EU average	47	0.829	0.048	0.737	0.913
GDP Growth *	47	0.024	0.014	-0.017	0.067
Employment 2013	47	62.393	9.146	43.2	75.5
Employment Growth *	47	0.014	0.012	-0.007	0.038

Less developed regions

Variable	Obs.	Mean	Std. Dev.	Min	Max
Initial GDP per capita relative to the EU average	66	0.559	0.140	0.277	0.780
GDP Growth *	66	0.036	0.013	0.003	0.067
Employment 2013	66	57.614	7.477	38.9	70
Employment Growth *	66	0.025	0.010	0.002	0.053

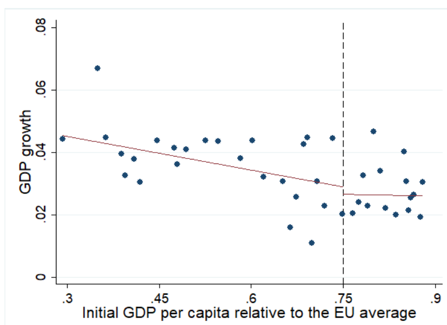
Note: * GDP growth is average annual growth in GDP per capita in PPS for the period of 2014-2016. Employment growth is average annual growth in the employment rate for the period 2014-2017. Initial GDP per capita relative to the EU average is measured in PPS and is the average over the period 2007-2009. Employment is the employment rate in 2013, the year before the start of the current budgetary cycle of structural funds.

transition regions and 2.5% for less developed regions. All differences around one standard deviation from the mean. A tentative difference in differences for developed and transition regions would therefore show an effect of transition region status on employment growth of 0.4% (1.4-1). This indicates there could be a real effect.

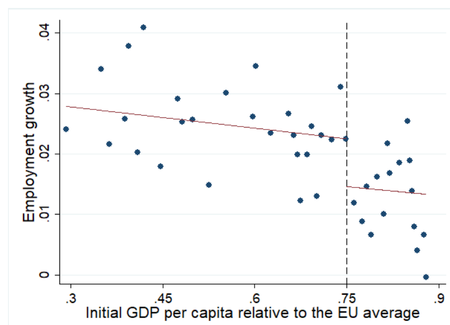
Comparing simple differences in growth between regions is however naive when these groups differ in important aspects. Table A.2 in the appendix shows summary statistics per treatment group for four control variables; population density defined as inhabitants per square kilometer, the median age of the total population, the share of tertiary educated of people aged 25-64 and the share of all employed that are employed in industry. These four variables are chosen because they are available on a regional level and could influence the outcome variables employment and GDP growth. For example, employment of higher educated tends to be less sensitive to changing business cycles than lower educated while employment in industry is more sensitive than other employment (Hoynes et al., 2012; Cairo, 2018). Table A.2 in the appendix shows that there are differences in the control variables between treatment groups except for the median age. All these differences are around one standard deviation.

In a RD-design however, differences in control variables among treatment groups do not pose a problem for any estimation as long as there is no jump in these control variables at the threshold and the variables are continuous. If there is a jump, the jump in the control variable could cause the jump in the outcome variable. In the next subsection it is shown in several ways that there are no jumps in control variables that cause any reason for concern. First we check in figure 4a to 4d if there is a jump in *outcome* variables rather than *control* variables because a jump in the outcome variable could suggest whether there is an effect suitable for an RD-design or not.

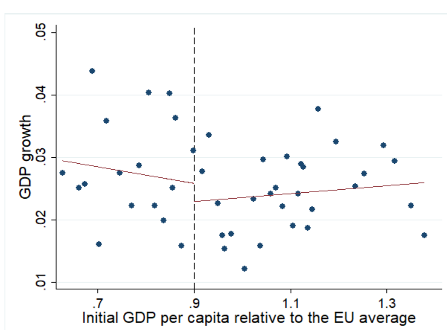
Figure 4: Visualization of discontinuity in outcome variables at the 75% and 90% threshold



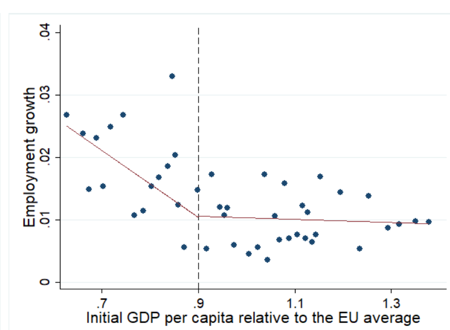
(a)



(b)



(c)



(d)

Note: GDP and employment growth are defined as average annual growth for 2014-2016 and 2014-2017 respectively. Initial GDP (PPS) is the average for the period of 2007-2009.

In figures 4a to 4d growth in GDP and employment is plotted as a function of initial GDP per capita. The figures contain equally sized bins and a plotted point could therefore obtain multiple observations or regions. A dashed line indicates either the 75% or 90% threshold. A plot of points could show straight away if there is a discontinuity, but a line is fitted trough the points on both sides of the thresholds to make make to make a comparison easier. The choice of the functional form of this line is often an empirical question (Jacob et al., 2012). In this research it is a linear functional form as this preference was elaborated in the methodology.

Although the lines on both sides of the 75% threshold seem to imply a small discontinuity in GDP growth this is not evident from the scatter plot alone. A few regions just below the 75% threshold have a much lower GDP growth than any of the regions above. But the relation ship between initial GDP per capita and GDP growth appears to downward sloping in accordance with convergence hypothesis discussed before.

Employment growth shows a stronger jump and discontinuity at the 75% threshold. This is evident from both the scatter plot and the fitted line. The figure therefore suggest using a RD-design to estimate the effects of funding. Over the whole range the relationship between employment growth and initial GDP per capita is downward sloping.

At the 90% threshold the fitted lines suggest a small jump an discontinuity in GDP growth. This is however less evident from the scatter plot alone and could be further explored by estimating the RD-design. Employment growth is higher for regions below the 90% but the plot of points could also represent a quadratic relationship between employment growth and initial GDP per capita. Visual interpretation of the data seems to suggest an investigation to the effect of structural funds on employment growth at the 75% threshold could be especially suitable for a RD design. The next subsection discusses the validity of the RD-design before the estimations of the effects of funding on the outcome variables are shown.

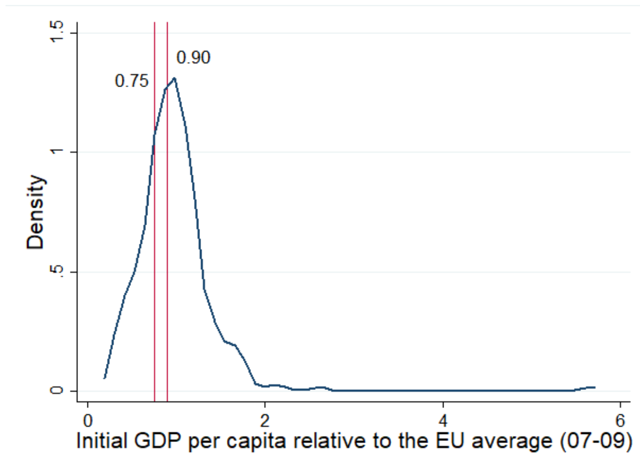
6.3 The validity of the RD design

In the methodology two issues were discussed that could potentially invalidate the RD-design; (i) manipulation of treatment and (ii) discontinuities in other covariates or control variables.

(i) It is possible to check for signs of manipulation by looking at the density plot of GDP per capita. If regions or authorities have manipulated the data on which eligibility is determined, this could be reflected in the data by a sudden jump in density on one of the sides of the thresholds (most likely the lower side as this makes regions eligible for extra funding). Figure 5 shows the density of regions as a function of GDP per capita.

Figure 5 does not show any sharp jumps on both sides of the 75% and 95% cutoff. There appears to be a small jump just above the 90% threshold but this is unlikely to be caused by any manipulation. The visual inspection of the density plot is complicated because the median of initial GDP per capita

Figure 5: Density plot of GDP per capita relative to the EU-average



Note: A density plot of regions against the assignment rule. The line on the left is drawn at 75% of regional GDP per capita relative to the EU average and the line right of it at 90%. The density plot uses a epanechnikov kernel.

relative to the EU average is around the cutoff of 90%. Because a median is a density-peak it could look like a jump on any side of the cutoff.

Besides looking for manipulation visually it is possible to use a formal test (McCrary, 2008). The McCrary density test tests the null hypothesis that states the rating variable (initial GDP per capita relative to the EU average (07-09)) is continuous at the threshold. Table 4 and figure 6a & 6b show the results of these tests.

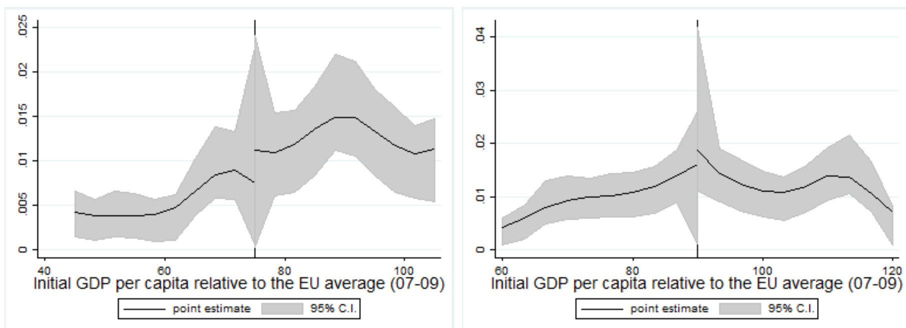
Table 4: Manipulation test (McCrary, 2008)

	Cutoff 90%		Cutoff 75%	
	left	right	left	right
Observations	116	148	66	198
Eff. Obs	36	35	26	32
Order est. (p)	2	2	2	2
Bandwidth est.	10%	10%	10%	10%
	P $\bar{0}$.403		P $\bar{0}$.848	

Note: Characteristics of the McCrary density test and the accompanying p-value for the null hypothesis that initial GDP per capita relative to the EU average is continuous.

With a p-value of 0.403 and 0.848 it is not possible to reject the null hypothesis that initial GDP per capita relative to the EU average (07-09) is continuous at the threshold of 90 and 75% respectively. It should therefore be concluded there is no evidence of manipulation of the data which could potentially harm the internal validity of the RD design.

Figure 6: Formal test of discontinuity



(a) at the 75% threshold

(b) at the 90% threshold

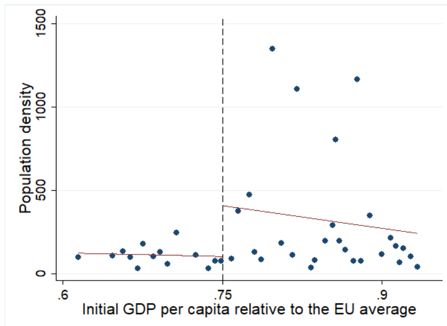
Note: Both figures show graphically the results of a McCrary density test (2008). In the test a histogram of the density is smoothed separately on both sides of the cutoff by using local linear regression. The 95% confidence interval of the regression line shows it is in both cases not possible to reject the null hypothesis that initial GDP per capita relative to the EU average is coninuous.

(ii) A second issue discussed that could potentially invalidate a RD-design is a discontinuity in any other covariates that could influence the outcome variables. The previously described control variables; population density, share of tertiary educated, employment share in industries and the median age, can be checked visually for a discontinuity by plotting regional 2013 values against the assignment variable. The covariates are fitted with a line in figures 7a to 7d for the threshold of 75%. Similar plots for the 90% threshold are depicted in the appendix in figures A.3a to A.3d.

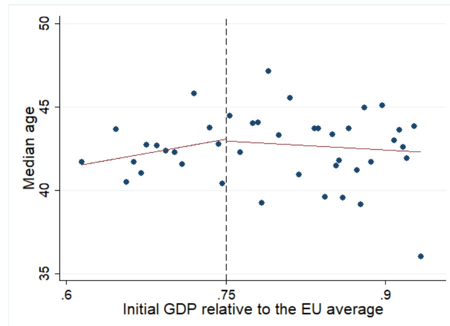
The share of employed in industry, share of tertiary educated and the median age do not show any concerning discontinuities at the threshold of 75% or 90%. A few regions just above the 75% and just below the 90% threshold have a higher population density. This appears as a small discontinuity but any discontinuity could bias the estimation treatment effects. For this reason the covariates are checked for a discontinuity in a more formal way.

A more formal way of checking for a discontinuity is estimating a jump in the covariates at the thresholds by using baseline equation 1 from the methodology. Instead of estimating this equation with the outcome variables GDP and employment growth it is estimated with control variables as if these are the outcome variables. When equation 1 is estimated with control variables, there should not be any significant jump at any of the two thresholds. The re-

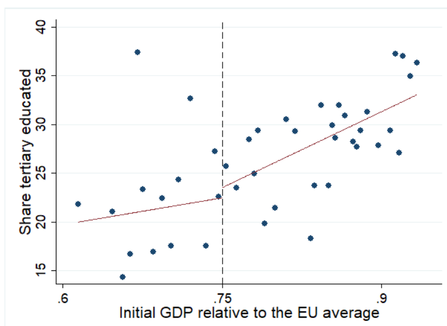
Figure 7: Visualization of discontinuity in covariates at the 75% threshold



(a)



(b)



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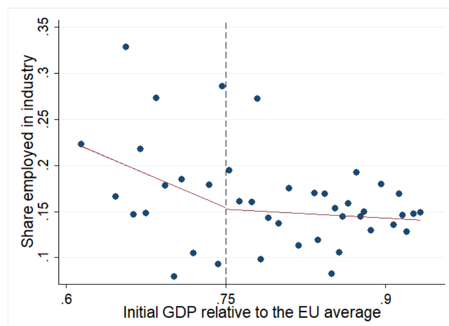

(d)

Note: The figures visualize four control variables for 2013 at the threshold of 75%; population density measured as inhabitants per square kilometer, the median age of the total population, the share of people aged 25-64 with tertiary education and the share of all employed that are employed in industry. Initial GDP per capita relative to the EU average is measured in PPS and averaged over 2007-2009. Dots represents equally sized bins rather than regional values to improve graph readability and could therefore obtain multiple observations.

sults of such an estimation are depicted in table A.4 in the appendix. For both thresholds, the estimations with the control variables as outcome variables do not show any significant jumps at the 5% level. For this reason it can already be concluded that the control variables are unlikely to bias the results of the RD-approach.

Because there is (i) no evidence of manipulation in the assignment variable and (ii) there are no discontinuities in four discussed control variables it can be concluded that the RD-design is internally valid. With the internal validity of the RD-design established it is possible to turn to the results of the estimations.

7 Results

The results are given in table 5 where the coefficient represents the jump at the discontinuity for both outcome variables at either threshold. The first results are estimated without the non-compliant regions so that the RD design is sharp (the data section showed there where four non-compliant regions at the 75% cutoff and thirteen at the 90% cutoff). The represented jump, or coefficient, in table 5 is from the group with a lower GDP to the group with a higher GDP and the treatment effect is therefore the reverse.

The baseline is estimated on a bandwidth of 10 percentage points on both sides of the threshold so that there is a minimum of 20 observations on both sides. The baseline is furthermore estimated with a triangular kernel and a linear functional form. Because there are two outcome variables and two thresholds of interest there are four baseline results.

Below the baseline results there are alternative specifications where the baseline is altered on one aspect to be able to say something about the robustness of the results. The baseline is either altered in the kernel (uniform or epanechnikov), the functional form (quadratic of cubic) or the bandwidth (data-driven, 5 percentage point or 15 percentage point). The data-driven bandwidth is chosen by a cross validation procedure that minimizes the mean-squared error of the local linear regression. The data-driven bandwidth is not the baseline because it often yields a very low number of observations.

Table 5 shows that the baseline estimation for the jump in average growth in the employment rate at the 75% threshold is -0.014. The result is significant at the 5% level. The effect of being assigned treatment on average annual growth in the employment rate is 1.4% meaning that the annual average growth in the employment rate is 1.4% higher for treated regions (treated = received the status of less developed regions because their initial GDP per capita is lower than 75% of the EU average). The result is robust in sign, size and significance for the choice of kernel. Both estimations using the epanechnikov or uniform kernel instead of a triangular one show an effect of 1.4% significant at the 5% level. The result is furthermore robust in size and sign for different bandwidths and the quadratic functional form. Only the estimation with a cubic functional form renders a lower estimate. From these results it appears that the effect of treatment on average annual growth in the employment rate is around 1 to 1.4%.

For the average annual GDP growth the baseline estimation estimates an effect of 2.1% at the 75% threshold. This result is significant at the 1% level. The other specifications estimate an effect between 1.5 and 4.5%. The effect appears to be robust in sign but the size varies. Three alternative specification are significant at the 5%. It could therefore be concluded that there is an effect of treatment between 1.5 to 4.5%. Treated regions (with a GDP per capita less than 75% of the EU average and the status of less developed region) benefit from funding with a higher GDP growth of 1.5-4.5%.

For the estimations at the 90% threshold there are no signs of an effect. For both the average growth in the employment rate and average GDP growth the

Table 5: Results

	75%		**90%**	
	Employment	**GDP**	**Employment**	**GDP**
Model	Coeff. (Std. Err.) (obs)	Coeff. (Std. Err.) (obs)	Coeff. (Std. Err.) (obs)	Coeff. (Std. Err.) (obs)
Baseline	-0.014 (0.007)** (53)	-0.021 (0.010)*** (53)	0.008 (0.011) (58)	0.009 (0.010) (58)
Variation kernel:				
Uniform	-0.014 (0.006)** (53)	-0.015 (0.009)* (53)	0.005 (0.008) (58)	0.009 (0.008) (58)
Epanechnikov	-0.014 (0.006)** (53)	-0.018 (0.009)* (53)	0.009 (0.009) (58)	0.009 (0.009) (58)
Variation bandwidth:				
Data-driven	-0.012 (0.009) (33)	-0.036 (0.018)** (22)	-0.042 (0.051) (18)	0.018 (0.012) (53)
5 percentage point	-0.010 (0.010) (22)	-0.037 (0.017)** (22)	-0.016 (0.029) (27)	0.012 (0.015) (27)
15 percentage point	-0.011 (0.006)** (69)	-0.015 (0.008)* (69)	0.002 (0.007) (85)	0.007 (0.007) (85)
Variation form:				
Quadratic	-0.011 (0.010) (53)	-0.039 (0.018)** (53)	0.004 (0.008) (58)	0.020 (0.017) (58)
Cubic	-0.004 (0.014) (53)	-0.045 (0.023)* (obs)	0.008 (0.014) (58)	0.041 (0.043) (58)

Note: The table shows the estimated jump in the average annual growth of the employment rate and GDP (per capita in PPS) at the 75% and 90% threshold. The baseline is estimated on all observations within a bandwidth of 10 percentage points below and above the cutoff point, a triangular kernel and a linear functional form. Other estimates are variations on the baseline with the kernel, bandwidth or functional form. All estimations are without control variables.
*, **, *** denote significance at the 10, 5 and 1% level respectively.

baseline estimation is smaller than 1% and positive. This implies, contrary than was hypothesized, growth rates are lower for regions just below the cutoff that are treated with the status of transition region. The estimated jump however varies in size and sign and is in no case significant. From the results in table 5 it cannot be concluded there are effects in either the growth in the employment rate or GDP at the 90% threshold.

The difficulty in estimating an effect at the 90% threshold could be caused by the removed non-compliant regions. Around the 90% threshold thirteen regions were excluded against only four at the 75% threshold. It is possible to use equation 2 where treatment is instrumented on the assignment rule to get estimations in a fuzzy RD design. This works as long as the probability of receiving treatment is different on both sides on the cutoff. Figure 3a and 3b in the data section showed already that the probability of receiving treatment is different on both sides of the cutoff. Treatment can be instrumented on the assignment rule in a first stage regression where the estimated treatment values are 'plugged' in equation 1 by means of a instrumental-variable regression (IV). This works best when the sample is large because the first stage from equation 2 requires a strong relation between the probability of treatment and the assignment rule. Only with a strong correlation and when the first stage equation is not a weak first stage, the estimated values for treatment can be used to estimate the baseline equation 1. Because the sample for this research is small, it is not expected that all effects from table 5 are significant in a fuzzy estimation. One would rather like to see estimates of the same size and sign.

The estimated values are used again to say something about the robustness of the results. The results of this fuzzy RD estimation are shown in table 6.

Table 6: Results of including non compliant regions with an IV

	75%		**90%**	
	Employment	**GDP**	**Employment**	**GDP**
Bandwidth	Coeff. (Std. Err.) (obs)	Coeff. (Std. Err.) (obs)	Coeff. (Std. Err.) (obs)	Coeff. (Std. Err.) (obs)
10 percentage point	-0.026 (0.019) (57)	-0.016 (0.019) (57)	- (-)	0.010 (0.038) (72)
5 percentage point	-0.021 (0.031) (26)	-0.050 (0.036) (26)	-0.008 (0.033) (38)	0.012 (0.013) (38)

Note: The table shows results for the baseline estimation including non-compliant regions by means of an IV-approach. The estimations are shown for two different bandwidths of 10 and 5 percentage points on both sides of the cutoff.
**, ** and * denote significance at the 1, 5 and 10% level respectively.

Results are only reported when the estimated instrument is not a weak instrument, meaning that the F-statistic of the first stage is larger than 10 and the instrument predicts positive treatment outcomes for regions eligible to receive funding.

The baseline result for the estimated effect on employment growth at the

75% threshold changes in an estimation with the instrumented non-compliant regions. The estimated effect of being assigned treatment on employment growth is between 2.1 and 2.6%. Although the estimations are not significant they add to the robustness of the earlier discussed baseline results as they have the same sign and a comparable size.

Similarly, is the estimation with non-compliant regions for the effect on GDP growth at the 75% threshold. The estimated effect is between 1.6 and 5% which is comparable to the baseline results in sign and a little less in size. The size however still indicates an effect and although the estimations are not significant they support the baseline results of table 5 that there is an effect.

At the 90% threshold there appear to be no effects of treatment (being assigned the status of transition region with GDP per capita between 75% and 90% of the EU average) on either the annual average growth in GDP or employment rates. For the annual growth in the employment rate a positive effect of 0.8% is estimated at the 90% threshold. This is however not significant and opposite to the baseline in table 5. For GDP a negative effect of treatment is estimated of 1 to 1.2%. A negative effect would imply that treated regions have lower GDP growth rates than untreated regions, which is contrary to what was hypothesized. However, the results are insignificant and it is therefore not possible to conclude that there are effects at the 90% threshold on either employment or GDP growth.

Because neither the results without non-compliant regions nor the results with the non-compliant regions included reveal any effect at the 90% threshold there is no evidence found in this research that treatment at the 90% threshold is effective. This would imply it is unnecessary to distinguish between transition and more developed regions in the EU regional policy as there are no effects of being assigned a transition region. However, there are treatment effects found at the 75% threshold which indicates that being assigned the status of less developed region is effective. It can therefore not be said that ESIF overall are ineffective. Possibly, the difference between the funding for transition regions and more developed regions is just too small to be effective. Or transition regions do not need extra funding as their authorities themselves could invest enough in policies or projects aimed at convergence different than less developed regions that cannot attract or supply enough investments themselves. As a consequence it could be argued that a distinction between less developed and more developed regions at the 75% threshold only is enough to execute the EU cohesion policy.

8 Robustness checks

Because none of the estimations at the 90% threshold reveal an effect this study continues with some sensitivity checks for the outcome variables at the 75% threshold only. The research continues with a sharp RD design, assuming again that the exclusion of 4 regions (two on either side of the cutoff) is justified. The estimated effects for the sharp RD in table 5 should not change when adding covariates if the research design succeeded in creating a valid control and treatment group.

Previous literature furthermore pointed out the importance of spatial dependence in estimating the effectiveness of European Strucutral and Investment funds. In a RD-design there is a quasi-experimental setting and spatial dependence is less likely a problem (Becker et al., 2010). Nevertheless it could be checked if the estimates are sensitive to the inclusion of spatial relations by incorporating higher order regional dummies on the NUTS level 1 where for example the Dutch NUTS level 2 regions Friesland, Groningen and Drenthe have the same dummy for the NUTS level 1 region Northern Netherlands (Harris, 2011). It is then assumed that these higher-level dummies capture any spillovers. In the bandwidths around the 75% cutoff however, 108 regions are distributed over 56 NUTS 1 regions and this set-up is not feasible for this research.

Another issue mentioned are spillovers from the Cohesion Fund. Although investment from the Cohesion fund is on a national level and has a different threshold it is mainly transferred to less developed regions and could therefore influence the effects estimated at the 75% threshold. It is possible to test whether the results are sensitive to the Cohesion Fund by adding dummy equaling 1 if a region is in a country that receives funding from the cohesion fund. Equation 3 is the baseline equation extended for sensitivity checks. The Cohesion Fund dummy is represented by CF_i, where CF_i equals 1 if NUTS 2 region i is in a country eligible to receive funding from the Cohesion Fund. The inclusion of such a dummy should not change the previously estimated effects.

$$Growth_i = \alpha_i + \rho_1 Treat_i + f(GDP09_i) + CF_i + \beta_1 X_i + \epsilon_i \tag{3}$$

In a similar fashion should the inclusion of any baseline covariates from 2013 not change the estimated effects. The four control variables diuscussed in the datasection are added to equation 3 in a vector of control variables X_i where x_i is the value of covariate x in region i.

A last thing tested in this analysis is the heterogeneity of effects. Because previous literature often found only conditional effects on employment the research tries to account for heterogeneous effects that differ based on a region's educational background. It is tested whether equation 3 yields different results when estimated for regions with a relatively high share of tertiary educated only. This could shed light on the conditionality of treatment effects. A high share is defined as a share of tertiary educated in the population above the median share, which is 20.3% in the entire sample around the 75% cutoff.

The results of the sensitivity checks are depicted in table 7. The sensitivity

Table 7: Sensitivity checks for the estimated effect at the threshold of 75%

	Employment	**GDP**
Model	Coeff. (St. Err) (obs)	Coeff. (St. Err) obs
Baseline	-0.014 (0.007)** 53	-0.021 (0.010)** (53)
With controls	-0.010 (0.007) (52)	-0.029 (0.010)*** (52)
Controlling for Cohesion Fund (CF)	-0.006 (0.007) (53)	-0.008 (0.010) (53)
Conditional on high educational attainment	-0.027 (0.008)*** (26)	-0.001 (0.014) (26)
Conditional on low educational attainment	0.001 (0.010) (27)	-0.043 (0.040) (27)
Conditional on high educational attainment and controlling for CF	-0.024 (0.007)*** (26)	0.008 (0.016) (26)
Conditional on low educational attainment and controlling for CF	0.012 (0.012) (27)	-0.028 (0.036) (27)
Excluding inner 0.03	-0.016 (0.013) (42)	0.014 (0.016) (42)
Excluding inner 0.05	-0.029 (0.016)* (31)	0.024 (0.032) (31)

Note: The table shows the estimated jump in the average annual growth in the employment rate and GDP (per capita in PPS) at the 75% threshold. The baseline estimation is estimated on the observations within a bandwidth of 10 percentage points below and above the cutoff point, a triangular kernel and a linear functional form. The other estimations are sensitivity checks for the baseline estimation. The second estimation controls for the four control variables described in the data section (median age, population density, share of tertiary educated and the share of people employed in industry all in 2013). The next estimation controls with a dummy for the Cohesion Fund. The jump is also estimated for regions having a high share of tertiary educated (above 20.3%, the median value) or a low share (below 20.3%) with and without controlling for the Cohesion Fund. The last two estimations exclude observations within either a 3 or 5 percentage point bandwidth, while maintaining other observations within the 10% bandwidth.
**, ** and * denote significance at the 1, 5 and 10% level respectively.

checks are performed on the baseline result with a triangular kernel, a bandwidth of 10% and a linear functional form.

For the average growth in employment rates the estimations do not change by adding the control variables separately (not shown in the table). When all controls are included in the baseline model the estimated jump at the 75% threshold is -0.010. Because it is a jump from below the threshold to above the treatment effect is again the reverse. The estimated effect of being assigned treatment on average annual employment growth changes to 1% where it was previously estimated to be around 1.4%. Although the estimated coefficient is not significant it is robust in size and sign. A similar story can be made for the inclusion of covariates in the estimations of the effect on average annual GDP growth. By including controls the estimated effect becomes 2.9% which is significant at the 1% level. Because the previously estimated effect was between 1.5 to 4.5% the effect is robust for the inclusion of covariates in significance, sign and size.

The baseline estimations are less robust when a control dummy for the Cohesion Fund is added. Although the estimations in the jump are of the same sign, the size of the coefficients is only half that of the baseline. Furthermore, these estimations are not significant. The estimations of the effect of treatment on growth in GDP and the employment rate could therefore be biased by the Cohesion fund as relatively more regions below the cutoff are in countries that receive funding from the Cohesion Fund. The cohesion fund an treatment status are positively correlated. The effects at the 75% threshold are therefore likely to be overstated as the cohesion fund might contribute to employment and especially GDP growth. It should be mentioned however that the Cohesion Fund is relatively small. The budget for the Cohesion Fund is 75 billion euro which is much lower than the 400 billion euro attributed to the funds that are used for treatment of less developed regions. It is therefore unlikely that there is no effect of treatment only because treatment is positively correlated with the eligibility for the Cohesion Fund although it should be kept in mind that the effect is probably slightly overstated.

The table shows results of separate estimations on regions with a higher and a lower share of tertiary educated people as well. The effects of being assigned treatment on the growth in the employment rate are 2.7% for regions with a high share of tertiary educated people. These results are significant at the 1% level while no effects are found for regions with the lower share of tertiary educated people. Both estimations, conditional on a low or high share of tertiary educated people, are estimated while controlling for the Cohesion Fund as well. The estimations appear to be robust for the inclusion of the Cohesion Fund. The effect of treatment on average growth in the employment rate conditional on regions having a high share of tertiary educated people while controlling for the Cohesion Fund is 2.4% which is significant at the 1% level. For this reason it is possible to conclude there is a positive effect of around 2.4 to 2.7% of the status of less developed region on growth in employment rates conditional on the region having a relatively high level of tertiary educated. Although it must be taken in to account that the sample size of this estimation is rather small, it seems that policy makers should take notice of the educational level of a region when using ESIF to achieve convergence.

The same can not be said for the effects of being assigned treatment on GDP growth rates. These are not significantly different for regions with either a high share or a low share of tertiary educated people. For both groups an insignificant positive effect is estimated.

The results of a last sensitivity are depicted in the bottom two lines of table 7. These lines show the results of a 'donut' regression where the inner observations close to the cutoff of 75% are excluded. When the inner observations within a bandwidth of 3 percentage point are excluded this leaves a bandwidth on both sides between 3 and 10 percentage point from the cutoff. If the exclusion of some observations within a certain bandwidth does not change the coefficients this adds to the robustness of the baseline results. However, the inner observations are important because an RD-design is concerned with the treatment effect at the cutoff. Excluding to much observations could give erroneous large estimates for a jump when the underlying relationship between variables is down or upward sloping.

The jump in the growth in the employment rate is estimated to be a -0.016 or -0.029 when the inner 3 or 5 percentage point of observations is excluded. The estimated effect of treatment on annual average growth in the employment rate is therefore 1.6 to 2.9%, of which the latter could be overstated by excluding to much observations at the center of the cutoff. The estimation for the growth in the employment rate however appears to be robust in sign and size when excluding the inner 3%. The effect of treatment on average annual growth in GDP per capita is not robust for the exclusion of observations within a range of 3 or 5 percentage point from the bandwidth.

The estimations for the effect on annual average growth in the employment rate and GDP per capita at the 75% thus appear to be robust for adding controls but not for the inclusion of the Cohesion Fund as control variable. The effect on annual average growth in the employment rate is significantly conditional on a highly educated population even when controlling for the Cohesion Fund. The number of observations to arrive at this conclusion is however small. In addition, the effect on the employment rate is robust for excluding inner observations contrary to the effect on GDP growth.

9 Discussion

Several aspects are important to consider in light of the results and the estimation techniques. These are the interference of the Cohesion Fund, the impossibility to control for spatial dependencies, the conditionality of treatment effects, the under use of funding in the current budgetary cycle and issues with the timing of effects.

The robustness section of this paper shows that estimated effects are not robust to the inclusion of a Cohesion Fund dummy. This is because relatively more regions below the cutoff are in countries that receive funding from the Cohesion Fund. Hence, the treatment and eligibility for less developed regions correlates with eligibility for the Cohesion Fund. The estimated effect of the status of less developed region on growth in the employment rate and GDP could also be caused by funding from the Cohesion Fund and the estimated effect could be biased. The Cohesion Fund however is relatively small compared to the other funds. Total funds available for the Cohesion Fund in the budgetary cycle of 2014-2020 are around 75 billion euros, against 120 billion for the ESF and 280 billion for the ERDF.[13] It could be argued it is unlikely the relatively small Cohesion Fund entirely invalidates the estimated effects in this research. In any case, the effects are likely to be slightly overstated because more regions in the treated group are in countries that receive funding from the Cohesion Fund.

In the robustness section it was furthermore not possible to check if there were spatial dependencies that could invalidate the results at the 75% threshold. Although it is unlikely that spatial dependencies play a role because of the quasi-experimental set up of a RD-design, it could in theory still be possible estimated results are not robust for spatial dependencies because there are important spill-overs neglected. It is difficult to figure out how that would hypothetically affect the results. Figure 1 showed how treated (less developed) and untreated regions (transition at the 75% threshold) are both located next to treated (less developed) regions. If treated regions below the cutoff of 75% benefit relatively more from spill-overs because they are close to other treated regions the RD-design still estimates the effect of treatment. If untreated regions above the 75% benefit relatively more from spill-overs the effect would simply be understated. Besides, Becker et al. (2010) already provided evidence that spatial dependencies are unlikely to play a role in an RD-design. It is because of these reasons unlikely that the estimated effects are invalid because of neglected spatial dependencies.

The last result from the robustness section to be discussed is the heterogeneity of treatment effects. In line with Mohl and Hagen (2011) it is found that treatment effects on the annual average growth in the employment rate are conditional on regions having a high share of tertiary educated people. Because the ESIF promote employment in general it is not really expected that especially regions with a high-skilled population benefit. It could be that ESIF supported

[13] See the public database on ESI funds: https://cohesiondata.ec.europa.eu/funds

investment is primarily beneficial to the employment of higher educated people because these policies are designed by higher educated people or that higher skilled people are especially adaptive to the requirements under which regional authorities may use ESI funding. No such conclusion can be made from this research however, and although the finding is significant at the 1% level and robust for the inclusion of the Cohesion Fund as control variable, the number of observations for it is low. It should therefore not be given too much value from this research alone.

Another issue is the under use of funds. In October 2018 the European Court of Auditors (ECA) voiced concerns about member states not being able to use all their assigned funds (ECA, 2018). It appears to be difficult for regions and nations to submit projects and apply for funding. This could either be caused by difficult criteria for the submittal of projects or inability to come up with the required resources to co-finance projects. Every project needs to fulfill certain criteria and needs to be financed by a regional or national authority for at least some degree. If regional or national authorities do not submit proposals there is of course no effect to be measured. The public database on the ESI funds shows that there is indeed a large under use of funding. This under funding differs a lot per country and fund. So did Slovenia only spend 5% of funds available in the ERDF while the Netherlands spent already 40% of funds available in the ESF. Especially Slovenia, Romania and Spain have difficulty spending all the funds (ECA, 2018). There is however no reason to think that under spending is influenced by the cutoff of 75%. Or in other words, it is unlikely regions just below or just above the cutoff differ in their ability to spend the funds. It is therefore possible to say that the estimated effects are not biased by the under use of funds, rather, effects would likely be stronger if all funds were spend. The estimated effects in this research are thus underestimated.

A last issue that briefly asks attention is the timing of effects. This research only covered four years of the current budgetary cycle. It was discussed that previous literature found effects sometimes only after three years and sometimes immediate. For this reason it is likely that effects are understated in the sense that the findings only concern short-term effects and not the effects of the entire budgetary period. The research could fairly easy be updated in later years when data for years up to 2020 is available. In that case it could be that the division between transition and more developed regions at the 90% threshold proves to have long-term effects.

10 Conclusion

This research estimated the effects of being qualified as either transition or less developed region on average annual growth in the employment rate and GDP for the current ESIF budgetary cycle up to 2018. It is shown that these effects could be estimated by a RD-design because assignment rules create treatment and control groups just above and below certain cutoff values.

The estimations show there is an effect of the status of less developed region on average annual employment growth of 1.4% and on annual average GDP growth (in PPS) of 2.1%. The effect on growth in the employment rate and GDP is robust for the inclusion of non-compliant regions in a fuzzy RD design. Both effects are robust for the inclusion of control variables, several regional characteristics initial to the treatment period. However, effects are not robust to the inclusion of a dummy for the Cohesion Fund and half in size when the Cohesion Fund is controlled for. Regions in countries that receive funding from the Cohesion Fund are overrepresented just below the 75% cutoff. It could be argued the Cohesion Fund doesn't bias the estimates too much as this is a relatively smaller fund but in any case the effect is likely to be slightly overestimated because of the Cohesion Fund.

Effects of the status of less developed region on average annual growth in the employment rate appear to be conditional on regions having a relatively high share of tertiary educated people. Even when controlling for the Cohesion Fund there is a significant effect of 2.4% of the status of less developed region on annual average employment growth for regions with a highly educated population. At the same time there is no effect of treatment on average annual growth in the employment rate for regions with a low share of tertiary educated people. It is therefore advisable that policy makers focus on education when trying to obtain convergence in employment rates. The current convergence policies seem to work best for regions with higher educated people. Policy makers that are concerned with ESI funding would therefore do best to design complementary policies aimed at human capital formation and educational development. The latter policies enhance the effectiveness of ESI funding in obtaining convergence. If policy makers would not use complementary policies they potentially even endanger the convergence effect of ESI funding. When funding is more effective for the higher educated regions and the higher educated regions are relatively richer, which seems like a reasonable assumption, lower educated regions are likely to lag behind even more in the future. The sample sizes in this research for estimations conditional on a highly educated population are however small and the results ask for further research.

Further research to the heterogeneity of treatment effects conditional on human capital could focus on the question whether these findings persist in a sample with more observations. If the findings of this research would be substantiated with other evidence it is possible to ask the question why ESI funding is more effective in creating employment growth for regions with a high share of tertiary educated people. For policy makers it is important and useful to know why employment effects appear to be particularly strong in higher educated regions because this gives the information needed to design efficient complementary policies.

The estimations of the effect of the status of transition region on annual average growth in the employment rate and GDP did not show any effects. At the 90% threshold no effect could be estimated either with or without non-compliant regions. This research therefore did not find any evidence on the effectiveness of treatment at the 90% threshold below which regions are assigned the status of transition region. However, because there are effects at the 75% threshold it cannot be concluded that ESIF overall are ineffective. Rather policy makers should rethink the division between transition and more developed regions. It could very well be that the authorities of richer transition regions close to the 90% cutoff can attract or supply enough funding themselves and that for this reason there is no need to support them in the framework of ESIF funding. Perhaps that the threshold could be lowered to 85% or 80% to save on ESIF expenditure. Or that even more could be saved when only one division between less developed and more developed regions at a 75% threshold suffices. A side note to this conclusion is that this research suffered from relatively more non-compliance at the 90% threshold than the 75%. Although this research used instrumented values of treatment to get rid of the bias, the small sample could make it difficult to uncover significant estimates with such a method.

Because this study investigates the current budgetary cycle of 2014-2020 while it is still underway it could already help policy makers in drafting up plans for the 2021-2027 budgetary cycle. Contrary to an ex-post evaluation after which decisions for the coming budgetary cycle have already been made. As a consequence of investigating the current time period, the estimated effects are only short-term effects. It could be that effects for a longer time period are different. It is advisable, and relatively easy to update this research in a later stadium (i.e. in 2020 or 2021) to give an answer on long-term effects of ESI funding in the current budgetary cycle. When redoing the study in 2021 it could be interesting to see how effects are different for different time spans in the current budgetary cycle. Do effects become stronger after more years or do they fade away? The answer would complement this research on the evaluation of ESIF effects in the current budgetary cycle and ultimately help policy makers with designing effective convergence policies.

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A Appendix

A.1

Table A.1: NUTS level 2 changes

2010	2013
EL11	**EL51** *(Code change)*
EL12	**EL52** *(Code change)*
EL13	**EL53** *(Code change)*
EL21	**EL54** *(Code change)*
EL14	**EL61** *(Code change)*
EL22	**EL62** *(Code change)*
EL23	**EL63** *(Code change)*
EL24	**EL64** *(Code change)*
EL25	**EL65** *(Code change)*
FR91	**FRA1** *(Boundary shift + recalculation)*
FR92	**FRA2** *(Code change)*
FR93	**FRA3** *(Code change)*
FR94	**FRA4** *(Code change)*
	FRA5 *(New region)*
SI01	
	SI03 *(Boundary shift + recalculation)*
SI02	
	SI04 *(Boundary shift + recalculation)*
UKI1 *(Split)*	
	UKI3 *(New region)*
	UKI4 *(New region)*
UKI2 *(Split)*	
	UKI5 *(New region)*
	UKI6 *(New region)*
	UKI7 *(New region)*

Note: The table shows changes in the NUTS level 2 classification of 2010 to 2013.

A.2

Table A.2: Summary statistics of regional control variables

All regions

Variable	Obs.	Mean	Std. Dev.	Min	Max
Population density	262	435.891	11173.319	3.4	10589.2
Median age	264	42.140	2.908	31.7	49.3
Share of tertiary educated	264	28.404	9.463	11.4	68.2
Share employed in industry	264	0.169	0.0683	0.012	0.371

Developed regions

Variable	Obs.	Mean	Std. Dev.	Min	Max
Population density	150	650.537	1502.746	3.4	10589.2
Median age	151	42.226	3.037	31.7	49
Share of tertiary educated	151	32.3	9.411	14.8	68.2
Share employed in industry	151	0.156	0.059	0.012	0.297

Transition regions

Variable	Obs.	Mean	Std. Dev.	Min	Max
Population density	47	209.632	362.648	11.5	2090
Median age	47	43.143	2.985	37.7	49.3
Share of tertiary educated	47	26.555	6.007	14	42.5
Share employed in industry	47	0.139	0.046	0.053	0.231

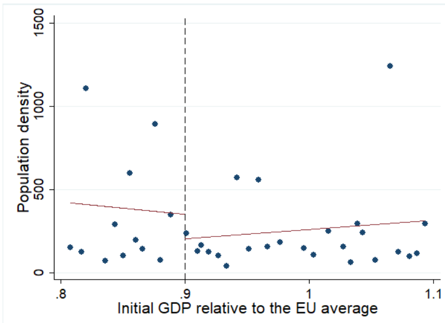
Less developed regions

Variable	Obs.	Mean	Std. Dev.	Min	Max
Population density	65	104.157	70.125	23.6	425.7
Median age	66	41.229	2.244	36	47
Share of tertiary educated	66	20.806	6.008	11.4	37.4
Share employed in industry	66	0.217	0.077	0.066	0.371

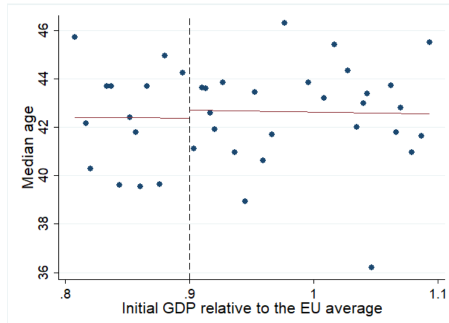
Note: The table shows summary statistics of control variables for all regions and by treatment group. Population density is the number of inhabitants per square kilometre. The median age is the median age of the total population. The share of tertiary educated people is the share of people aged 25-64 with a tertiary education. The share of employed in industry is the share employed in industry (NACE rev. 2 activities category B to E) out of all employed.

A.3

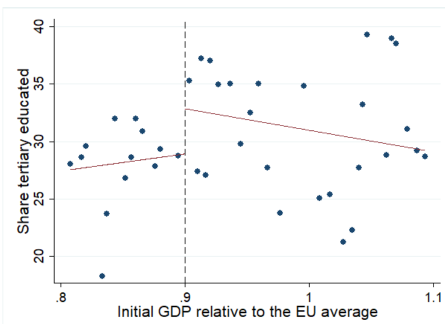
Figure A.3: Visualization of discontinuity in covariates at the 90% threshold



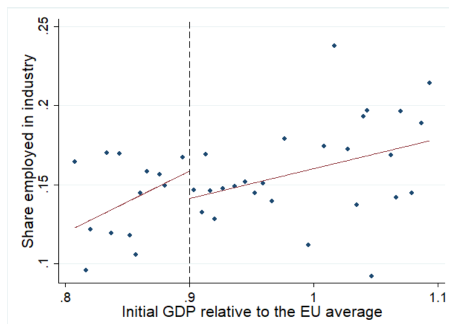
(a)



(b)



(c)



(d)

Note: The figures visualize four control variables for 2013 at the threshold of 90%; population density measured as inhabitants per square kilometer, the median age of the total population, the share of people aged 25-64 with tertiary education and the share of all employed that are employed in industry. Initial GDP per capita relative to the EU average is measured in PPS and averaged over 2007-2009. Dots represents equally sized bins rather than regional values to improve graph readability and could therefore obtain multiple observations.

A.4

Table A.4: Regression estimates of the jump at the 75% and 90% threshold using the control variables as outcome variables

	75%	**90%**
Dependent variable:	Coeff. (Std. Err.) (Obs)	Coeff. (Std. Err.) (Obs)
Population density	174.360 (98.892)* (52)	-125.99 (159.67) (58)
Median age	1.742 (1.931) (53)	0.883 (2.043) (58)
Share tertiary educated	5.150 (3.451) (53)	3.668 (2.790) (58)
Share employed in industry	0.011 (0.055) (53)	0.005 (0.023) (58)

Note: The table shows estimations of the jump at the 75% and 90% threshold for four covariates described in the data section; the regional population density measured as inhabitants per squared kilometre, the median age of the total regional population, the share of tertiary educated among people aged 25-64 in the region and the share of all employed that are employed in industry (using the NACE rev. 2 classification system where all activities B to E are classified as industry). All variables are from 2013, before the start of the budgetary period. The regression model is similar to the baseline model (with a bandwidth of 10 percentage point, a triangular kernel and a linear functional form) but uses the four covariates as outcome variables. The rating variable is, similar to the baseline model, initial GDP per capita relative to the EU average in the period 2007-2009.
**, ** and * denote significance at the 1, 5 and 10% level respectively.