Place-Based Policies and Inequality Within Regions

Valentin Lang *University of Mannheim*
Nils Redeker *Jacques Delors Centre, Hertie School Berlin*
Daniel Bischof *Aarhus University & University of Zurich*

August 3, 2022

Abstract

Against the backdrop of rising inequality across regions, place-based policies have become an increasingly popular tool to support "left-behind" places. While existing research provides evidence for average growth effect of such policies, little is known about their distributional effects within regions. We compile a new panel data set on income inequality across and within regions in the European Union (EU), based on household data from more than 2.4 million respondents of national surveys and covering a maximum of 231 European regions in the 1989-2017 period. These data show that inequality within regions is substantial, tends to increase over time and contributes more to inequality in Europe than inequality across regions. We then study the distributional effects of one of the world's largest placed-based policies, the EU Cohesion Policy, on household incomes. For causal identification we use, first, a discontinuity in disbursed amounts that results from EU eligibility criteria and, second, a difference-in-differences design. We find an economically substantial, positive effect of EU funds on household incomes that is larger at the top of regional income distributions than at the bottom. The place-based policy increases inequality within regions. To understand the policy's mechanisms, we differentiate by production factors, sectors, and education levels with macro and micro data and find that these effects are driven by higher labor incomes for more highly educated individuals in multiple sectors. In sum, these results suggest that place-based policies can be effective for reducing inequality across regions but in the supported regions tend to lift the incomes of the rich rather than those of the poor.

Authors' emails: lang@uni-mannheim.de, redeker@delorscentre.eu, db@danbischof.com. We thank participants at conferences of the Society for the Study of Economic Inequality (ECINEQ), the European Public Choice Society (EPCS), the European Political Science Association (EPSA), the Global Research in International Political Economy (GRIPE), the Political Economy of International Organization (PEIO) as well as seminar and workshop participants at Paris Sorbonne University, Paris Dauphine University, the University of Bergen, the University of Goettingen, Heidelberg University, Hertie School Berlin, MPIfG Cologne, ZEW Mannheim and the University of Mannheim. Melanie Backes and Leonhard Xu provided excellent research assistance. Daniel Bischof acknowledges funding from the Swiss National Science Foundation (SNF Ambizione Grant, No. 179938).

1 Introduction

Placed-based economic policies have become ubiquitous. As globalization, technological change and other structural shifts increasingly concentrate economic activity in certain places (Autor, Dorn, and Hanson 2013; Gaubert et al. 2021; Dauth et al. 2022), policymakers are using more and more resources to counter the rise of economic hardship and political frustration in the places that are left behind (Autor et al. 2020; Bisbee et al. 2020; Broz, Frieden, and Weymouth 2021; Colantone and Stanig 2018*a*,*b*,*c*). The US government, for example, spends about USD 60 billion per year on regional economic policies (Bartik 2020) and the European Union (EU) recently increased its budget for regional development to about EUR 373 billion until 2027. However, despite their wide and growing usage, we know little about *who benefits from place-based policies.*

A growing literature finds that regional funds and place-based policies can promote regional economic growth and benefit local incomes, productivity and employment (Becker, Egger, and von Ehrlich 2010; Busso, Gregory, and Kline 2013; Reynolds and Rohlin 2014; Seidel and Von Ehrlich 2018; Criscuolo et al. 2019). So far, however, this research has mainly studied *average* effects (for literature reviews, see Ehrlich and Overman 2020*a*; Kline and Moretti 2014*a*; Moretti 2022). In contrast, we lack evidence on how benefits from place-based funding are distributed within supported regions (Bartik 2020; Neumark and Simpson 2015).[1] This is particularly important because, as we show, income differences within regions remain large. Just like not all people in prosperous regions are rich, not all people in left-behind regions are poor. To know whether placed-based policies actually support left-behind people in left-behind places or redistribute resources to the rich in these regions we need to study how gains from these policies are distributed within regions.

In this paper, we study the distributional effects of one of the world's largest place-based policies in the context of Europe. As a first step, we construct a new data set on inequality across and within European subnational regions.[2] We collect and harmonize household-level income data from a large set of national household surveys and more than 2.4 million survey respondents in Europe. This gives us a panel of intra-regional income distributions across 231 European regions in the 1989-2015 period. These data allow us to identify new stylized facts on the development of income inequality in Europe

[1]Neumark and Simpson (2015: p. 76) conclude their extensive literature with the statement that: "the evidence that place-based policies achieve their distributional goals is itself far from clear." See also Bartik (2020: p. 110).

[2]We apply the EU's 'NUTS2' definition of a region. NUTS2 regions cover between 0.8m and 3m inhabitants.

across and within regions since 1990.

As a second step, we use our original data set to study how a large-scale, place-based EU policy affects the distribution of household incomes across and within regions. We use newly available information on the EU's Cohesion Policy to examine how these regional funds influence the intra-regional income distribution. EU rules mandate that the bulk of regional funding goes to regions with a GDP per capita below 75 percent of the EU average. For identification, we rely on this eligibility criterion in two different ways. First, we estimate a fuzzy regression discontinuity design (RDD) around the funding threshold to compare barely eligible with barely ineligible regions. Second, we make use of the fact that the EU's Eastern enlargement decreased its average GDP per capita while the 75-percent-rule stayed in place. As a result, several regions lost their eligibility status for reasons unrelated to the their own economic development. We use this alternative set-up to study the temporal dimension of the policy's effects in a difference-in-differences (DID) design. The two identification strategies yield consistent results and show how gains from the place-based policy are distributed across households in the European income distribution. In a third and final step, we study the mechanisms of the main effect by combining the household-level data with macroeconomic data from national accounts and with individual-level data from surveys. This allows us to disaggregate effects by production factors, sectors, and skill level and to explain the causes of the policy's distributional effects.

We reach the following main conclusions. First, intra-regional inequality in the EU is substantial: Overall inequality in Europe is driven more by inequality within regions than by inequality across regions. In almost all poor regions, the richest decile is richer than the poorest decile in the richest regions. Over time, we observe a mild increase in inequality within regions. Second, our results show that the place-based funds increase the regional mean of disposable household income. With our micro-level data, we find similar effects as when examining regional economic growth, as reported in national accounts. Our estimates point to a fiscal multiplier of about 1. Third, EU funds benefit the relatively 'rich' in supported regions more than the relatively 'poor.' While rich households in eligible regions see substantial increases in income, effects on poorer households are statistically not distinguishable from zero. In line with these results, we also find that EU funds significantly increase intra-regional inequality as measured by intra-regional Gini indices and percentile ratios.

To explain these main results, we then study the mechanisms behind these effects. There are multiple reasons why place-based policies may help the rich rather than the poor in supported regions. First, they could benefit capital more than labor (Alder, Shao, and Zilibotti 2016). Often coming in the form of investment subsidies and tax credits, place-based policies could increase returns to capital. Depending on the elasticity of substitution between capital and labor in supported firms, new capital investments could also substitute labor. As a consequence, the place-based policies could increase capital gains of firms more than their wage bill and, thus, primarily work to the advantage of capital holders at the upper end of the local income distribution (Bartik 2020). Second, even if place-based policies benefit labor, it is unclear which types of jobs they create and whose wages they increase. If place-based policies, for example, aim at high-paying sectors with large growth multipliers they could put upward pressure on high local wages without benefiting lower income workers (Bartik 1991; Reynolds and Rohlin 2015; Liu 2019). Third, accessing place-based policies can require upfront investments. Firms and individuals need to acquire knowledge about policies and face costs when applying for support and administering subsidies. Larger and more productive firms that employ high-skilled workers are likely to be in a better position to carry these costs than firms with less (human) capital. As a result, place-based policies might benefit high-skilled workers more than low-skilled workers at the bottom of the income distribution. We study these mechanisms by differentiating between production factors, sectors, and skill levels. The results show that the growth-enhancing and inequality-increasing effects are due to increasing household incomes from labor rather than from capital (or from public transfers). Macro-level evidence shows that the policy leads to rising investment and employment in multiple and diverse sectors; the increase in local inequality is not driven by a concentration on the highest-paying sectors. Individual-level evidence demonstrates that, instead, income gains differ by skill level. The place-based policy increases the incomes of highly educated individuals much more than it increases the incomes of less educated individuals. Evidence from surveys among beneficiaries in supported regions confirms this conclusion.

With these results, our paper contributes to three strands of literature. First, we add to the literature on the trajectory of economic inequality in advanced economies (Alvaredo et al. 2013; Piketty 2014; Lakner and Milanovic 2016; Hammar and Waldenström 2021) with a focus on its spatial dimension (Gaubert et al. 2021; Iammarino, Rodriguez-Pose, and Storper 2019). To the best of our knowledge, we provide the first detailed panel data set on the development of income inequality *within* European subnational regions. Our data allows us to, for the first time, decompose inequality in Europe into a cross-regional and an intra-regional component. Importantly, we show that intra-regional inequality remains substantial and has become an increasingly important component of overall European inequality in the last decades.

Third, we advance the existing literature on the effects of place-based policies by studying their distributional effects. The growing political interest in providing economic support to left-behind regions, has sparked a wave of research on the effects of such policies. One strand of this literature estimates welfare effects of place-based policies using structural spatial equilibrium models (Glaeser and Joshua 2008; Kline and Moretti 2014*b*; Fajgelbaum and Gaubert 2020; Gaubert 2018; Gaubert, Kline, and Yagan 2021). These studies have so far abstracted from the welfare implications of intra-regional distributional effects of cross-regional redistribution. Another strand of this literature applies empirical methods for causal inference to study the economic effects of individual place-based policies in the US, (Busso, Gregory, and Kline 2013; Kline and Moretti 2013, 2014*a*; Reynolds and Rohlin 2014) in Germany, (Seidel and Von Ehrlich 2018; Henkel, Seidel, and Suedekum 2021; Siegloch, Wehrhöfer, and Etzel 2021), in the UK and (Criscuolo et al. 2019) and in the EU (Becker, Egger, and von Ehrlich 2010, 2012, 2013, 2019; Ehrlich and Overman 2020*b*; Albanese, Barone, and Blasio 2021; Dellmuth 2021). The bulk of these studies find positive effects on overall growth, productivity, and employment. Our study also finds such aggregate gains but goes beyond these results by providing evidence on how these gains are distributed within regions and thus highlights a distributional dimension of place-based policies that the literature has so far largely ignored. An exception in the existing literature is Reynolds and Rohlin (2015) who study distributional effects on local household incomes of US federal Empowerment Zones between 1994 and 2000. Like our study, their research suggests that the policy increased inequality in supported areas. Compared to their paper, we study discretionary public funding rather than tax incentives, focus on a substantially larger program for a longer period of time, and make use of quasi-exogenous variation rather than conditioning on observables for causal identification. Our result on the mechanism behind this distributional effect aligns with previous findings that more productive firms often are more likely to receive place-based funds in many contexts (Bachtrögler et al. 2019; Bartik 2020; Slattery and Zidar 2020). Moreover, the finding also resonates with the perspective that such policies are more effective for recipients with higher levels of education (Becker, Egger, and von Ehrlich 2013; Ehrlich and Overman 2020*a*). While existing results demonstrated this for heterogeneity of the aggregate effect *across* recipient regions, our results show that differences in effects by education level *within* regions explain why these policies benefit the rich rather than the poor.

The remainder of this study proceeds as follows. In section 2, we present our new data set on inequality within and across European subnational regions. In section 3, we describe the place-based policy that we study as well as our identification strategy based on the RD design. Section 4 presents our main results. Section 5 examines the mechanisms behind the distributional effects we find. Section 6 studies the temporal dimension of the effects based on an alternative DiD identification strategy. Section 7 discusses implications and concludes.

2 Inequality Across and Within Regions: Data for Europe

This study provides the first comprehensive data set on income inequality within European regions. It covers a panel of 231 European regions in the period between 1989 and 2015. To compile this data set, we combine and harmonize household-level data from 260 national household surveys covering a total of 2.4 million survey respondents. In this section, we, first, describe data collection and data processing and, second, present the main stylized facts and trends on inequality across and within European regions.

Definition of regions. Our definition of a European region follows the EU's NUTS2 geocode standard.[3] A NUTS2 region is the second level of subnational administrative units (below the first subnational level, NUTS1, and the national level, NUTS0). We choose the NUTS2-level because it is the smallest unit for which data coverage is sufficient and because eligibility for the EU's place-based policies is assigned at this level .[4] A NUTS2-region corresponds to, e.g., a *Regierungsbezirk* in Germany, a *région* in France, a *regione* in Italy, and a *comunidad autónoma* in Spain. Compared to many other country-specific subnational administrative units, the NUTS2-standard ensures that regions are of similar size across Europe. According to the definition, each country's average NUTS2-region is

[3] The acronym NUTS stands for *Nomenclature des Unités Territoriales Statistiques.*

[4] We use the NUTS definition from 2016, which was active at the end of our observation period. At this time, there were 281 European NUTS2-regions.

supposed to be home to 0.8 - 3 million inhabitants.[5]

Data sources. To measure the distribution of incomes within European regions, we require household-level data with sufficiently fine-grained geographical identifiers. We collect such data from various sources. First, we use a total of 86 national surveys that are provided by the Luxembourg Income Study (LIS). The main advantage of LIS is the harmonization of income surveys across countries and over time. The surveys that LIS provides are based on a uniform set of assumptions and definitions of income concepts and a harmonization that maximizes the comparability of the underlying survey data. This is why LIS has a "reputation as the gold standard of cross-nationally comparable inequality data" (Solt 2016: 1268). Since LIS does not harmonize geocodes according to the NUTS standard, we implement such a harmonization by hand for the 86 surveys for which this is possible. This yields data for regions in Austria, Estonia, Greece, Hungary, Ireland, Italy, Lithuania, Poland, Sweden, and Slovakia. For the remaining European countries LIS does not include sufficiently fine-grained geocodes.

Our second data source are national household surveys provided by the EU's Statistics of Income and Living Conditions (EU-SILC). EU-SILC is a yearly EU-wide survey that provides detailed data on household incomes under a common framework that maximizes comparability across countries and over time. As EU-SILC started in 2003, we only use EU-SILC surveys when no adequate LIS survey is available. In total, we use 135 national household surveys provided by EU-SILC for regions in Croatia, Cyprus, Czechia, Finland, France, Luxembourg, Latvia, Malta, and Spain.

For Germany and the United Kingdom, the two largest EU member countries in the observation period, neither LIS nor EU-SILC provide survey data with sufficiently fine-grained geographical identifiers. We thus resort to national sources for these two countries. For the United Kingdom we use data from both the British Household Panel Survey (BHPS) and from Understanding Society; for Germany we use the Socio-Economic Panel (SOEP). Both are large-scale national, yearly surveys that include fine-grained geographical identifiers (at least in the restricted-use versions, which we acquired).

By combining these 260 household surveys, we use data from about 2.4 million survey participants.

Data harmonization. In each of the 260 household surveys that we collect, we apply the following approach. First, in order to assign households to NUTS2-regions, we harmonize the geographic identi-

[5]Countries with fewer inhabitants consist of a single NUTS2 region.

fiers of the surveys according to the NUTS2 definition of 2016. This harmonization was implemented by hand and takes account of all administrative reforms in the observation period. We only keep observations for which it was unambiguously possible to map observations into the 2016 definition of NUTS2 regions.

To compare incomes across households of different size, we follow the latest OECD recommendation in applying the "square root scale" and divide the household income by the square root of household members.[6] For incomes that are reported to be negative, we follow LIS's recommendation and set them to zero. To compare incomes across countries and over time, we adjust them to 2011 international dollars to achieve purchasing power parity (PPP). We do this by first applying a national consumer price deflator to incomes reported in current local currency units (LCU) in order to express them in terms of 2011 prices. We then convert these values (constant LCU) to international dollars using the World Bank's data on 2011 PPP.

Our main income measure is disposable income, i.e., the income that people have available for consumption or saving, defined as total income minus income taxes and contributions – it is the most commonly used measure in the related literature. All surveys that we use include this standard measure and apply very similar definitions for calculating it. For examining mechanisms and robustness, we also use alternative income concepts such as total income, labor income, and capital income. We describe these further below.

For all income concepts, we calculate the following measures on the region-year level:

- Mean incomes
- Mean incomes for the ten deciles by disposable income
- Incomes at the 10^{th}, 20^{th}, ... , 90^{th}, and 95^{th}, 99^{th} percentile
- Percentile ratios (P90/P10, P80/P20)
- Gini coefficients

As we consider large surveys, they cover a large number of households in most regions and years. The mean number of households per region-year is N=1034. Figure SI 4 in the Appendix plots a histogram of the number of survey respondents per region-year and shows that some region-year statistics are based on a relatively small number of survey responses. To address the concern that small samples distort aggregate measures, we exclude region-year-specific measures that are based on

[6] http://www.oecd.org/els/soc/OECD-Note-EquivalenceScales.pdf

less than 500 respondents.[7] In total, the data cover a maximum of 231 regions in the 1989-2017 period. Data is not available for all regions in all years, as some of the surveys only start in the 1990s or 2000s. Furthermore, gaps between two LIS-harmonized surveys are sometimes larger than one year. For the years between two LIS-harmonized surveys, we linearly interpolate the region-year-specific measures (but we do not extrapolate). The surveys from SILC, BHPS, Understanding Society, and SOEP are conducted every year. In total, we record income data based on household-level data for 4104 region-year observations.

Patterns and Trends of Regional Inequality in Europe

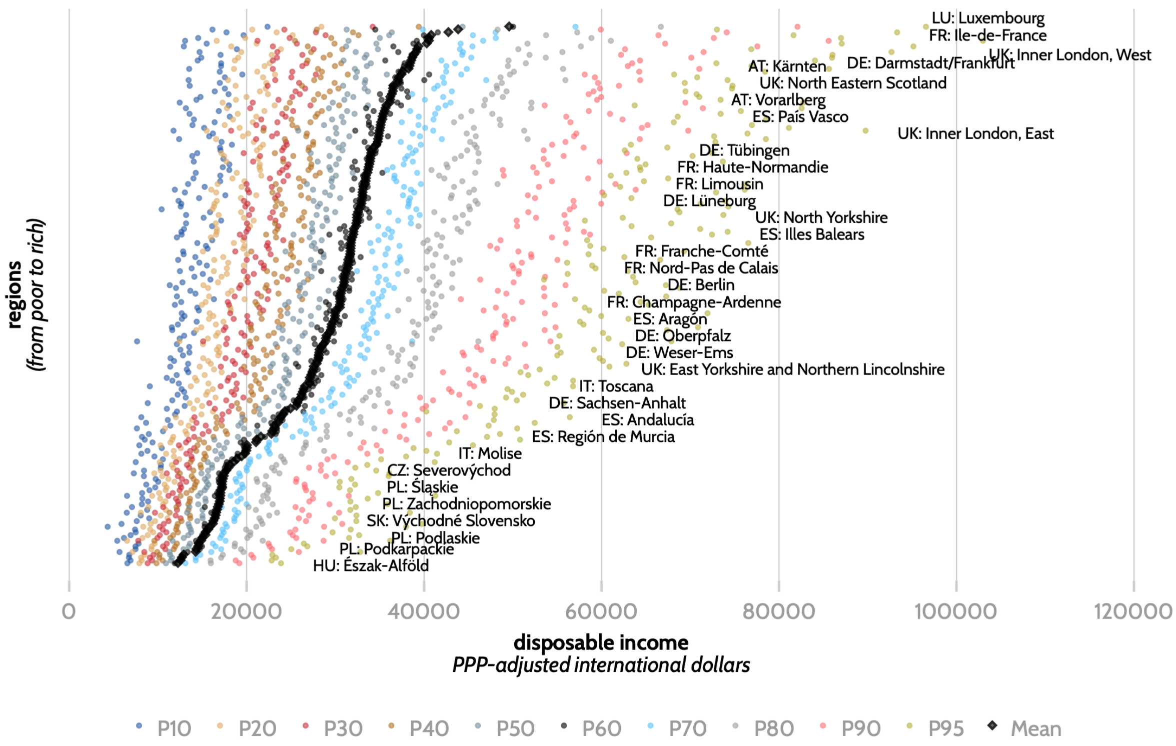
This new data set allows us to analyze inequality in Europe from new perspectives. Perhaps most importantly, we can examine inequality within regions and compare these intra-regional income distributions across regions. Figure 1 provides a first visualization of the data. It plots the disposable income of different percentiles of the within-region income distribution across European regions.

The regions are ordered by mean disposable household income. The richest regions (at the top) include Luxemburg, the greater Paris area ("Ile-de-France"), London, and the greater Frankfurt area in central Germany ("Darmstadt"). Among the poorest regions with data (at the bottom) are regions in Poland, Hungary, Southern Italy, and in the Baltics. [8] Mean disposable household incomes in the richest regions exceed those in the poorest regions by a factor of 4. What stands out in the graph is the large spread of incomes within regions. We consider it particularly noteworthy that even in the richest regions, many people have a lower disposable income than the median in relatively poor regions. In other words, most regions are home to a significant number of relatively poor people. At the same time, even in the poorest regions, the richest incomes surpass those at the bottom of the income distribution in rich regions. In other words, many people in poor regions are, by European standards, relatively rich. Overall, while the graph shows important differences in disposable income across European regions, it also highlights that income inequality within regions is substantial.

How large is inequality within regions and how does within-region inequality vary across Europe? We plot regional Gini indices in Figure 2 to visualize regional patterns. Regional Gini indices average at around 0.30 and are thus similar in size to the national Gini indices of European countries. There is,

[7] In robustness tests, we show that results do not depend on this choice, see SI.5.5.
[8] Note that data for regions in Romania and Bulgaria are missing.

Figure 1: The income distribution within European regions



Notes: The figure plots annual disposable household income of various percentiles of the intra-regional income distribution, latest available year.

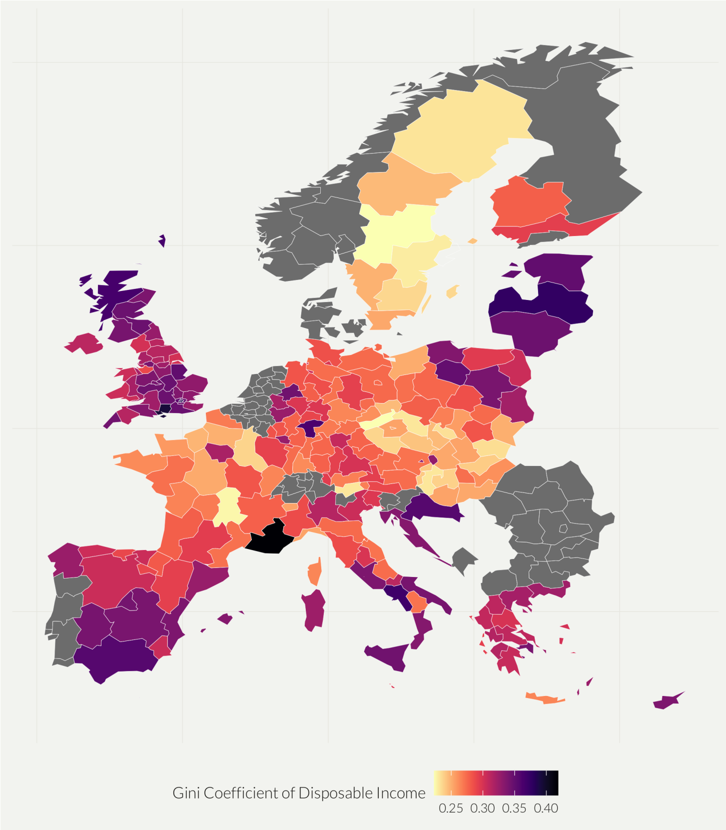
however, substantial regional variation. First, the most unequal region in the EU is the French region of Provence-Alpes-Cote d'Azur with a regional Gini of 0.40.[9] The most equal region is the North West of the Czech Republic (Severozapad) with a regional Gini of 0.22. Second, regions in more unequal countries tend to be more unequal than regions in more equal countries. For instance, intra-regional inequality is high in the UK, aligning with the fact that the UK is among the most unequal countries in Europe. Conversely, regions in the relatively egalitarian Sweden are among the most equal European regions. Third, however, there are also important differences within countries. In both Spain and Italy, the poorer Southern regions are more unequal then the richer Northern regions. [10]

How important is inequality within regions relative to inequality across regions? To compare these two dimensions of inequality we decompose total European inequality into the two components.

[9] A potential explanation for this could lie in the income differences between a rich coast (St. Tropez, Cannes, Nice) and a poorer, rural hinterland.

[10] In the Appendix, we examine the relationship between regional mean income and regional inequality and find a weak positive association (see Figure SI 1). But while richer regions tend, on average, to be somewhat more unequal, there also exist relatively unequal, poor regions and relatively equal, rich regions.

Figure 2: Regional Gini indices



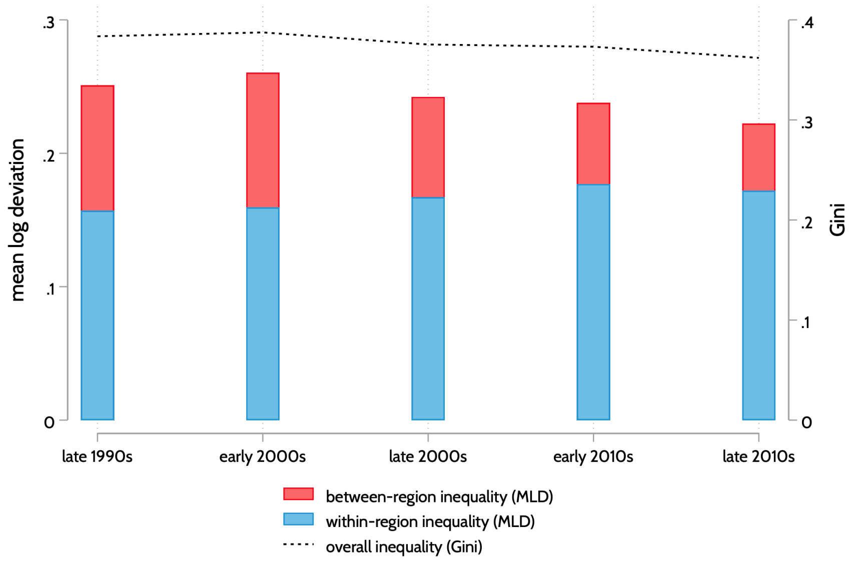
Notes: The map shows regional Gini indices of disposable household income, latest available year.

For this purpose, we require an inequality measure that is additively decomposable and use the mean log deviation (MLD or GE(0)).[11] In Figure 3 we implement this decomposition and add the time dimension to the analysis. The figure plots the evolution of the between-region and the within-region component of European inequality as measured by the MLD between the late 1990s and the late 2010s.[12] It also shows that overall inequality in these regions, as measured by the Gini coefficient, ranges between 0.362 and 0.387 with a slowly decreasing trend. Importantly, the graph shows that inequality within NUTS2-regions contributes more to European inequality than inequality across these regions. Furthermore, while between-region inequality has declined over time, within-region inequality has been increasing over the last 25 years. Our focus on inequality within regions thus corresponds to the growing importance of such inequality in Europe.

[11] See Lakner and Milanovic (2016); Hammar and Waldenström (2021) for similar decompositions of *global* inequality into its between-country and within-country components.

[12] Note that we fix the sample of regions for this exercise to ensure comparability over time. This means that regions from countries that join the EU later and regions with missing data are not included.

Figure 3: Decomposing European inequality between and within regions



Notes: The figure plots the between-region component and the within-region component of European inequality. Each regional distribution is represented by 10 deciles groups. The height of the bars indicates the level of inequality as measured by the mean log deviation (MLD or GE(0)), an additively decomposable inequality measure. The visualization is inspired by Lakner and Milanovic (2016) and World Bank (2016), who apply a similar approach to decompose global inequality into within-country and between-country components.

3 Empirical Setting: The European Structural and Investment Funds

The EU administers one of the world's largest place-based policies. For the 2021-2027 funding period, the EU agreed on structural and investment funds for "economic, social and territorial cohesion" worth 392 billion euro.[13] The volume of this policy's yearly disbursements is thus comparable to the combined volume of all place-based policies in the United States including tax incentives (approx. USD 60 billion, see Bartik 2020). According to the European Commission, these funds aim to "reduce the economic, social and territorial disparities that still exist in the EU." [14] A wide range of private-sector and public-sector projects that aim to promote economic development are eligible to receive such funds. Eligible organizations[15] must submit project applications that meet the selection criteria of specific "operational programs" and will then receive financial support with a maximum co-financing

[13] https://cohesiondata.ec.europa.eu/stories/s/2021-2027-EU-allocations-available-for-programming/2w8s-ci3y/
[14] https://ec.europa.eu/regional_policy/index.cfm/en/policy/what/investment-policy/
[15] "Organisations that can benefit from regional funding include public bodies, some private sector organisations (especially small businesses), universities, associations, NGOs and voluntary organisations. Foreign firms with a base in the region covered by the relevant operational programme can also apply, provided they meet European public procurement rules." https://ec.europa.eu/regional_policy/en/funding/accessing-funds

rate of up to 85 percent.[16]

Our focus is on the two largest types of EU funds, because their allocation follows an institutional rule that we can exploit for identification: The European Regional Development Fund (ERDF) and the European Social Fund (ESF).[17] The ERDF is advertised as aiming to "strengthen economic, social and territorial cohesion in the EU by correcting imbalances between its regions,"[18]. The official headline goal of the ESF is to "improve the situation of the most vulnerable people at risk of poverty"[19] and thus explicitly aims to target the poor in the supported regions.

A new data set on funding disbursements under the EU regional development and cohesion policy in the 1989-2017 period was published by the European Commission in 2020 and – according to the European Commission (2019) – constitutes "the most comprehensive record yet" of this policy.[20] In Figure 4, we give an impression of the volume of these funds by visualizing the per capita amounts disbursed to individual regions between 1989 and 2017. As is visible, these are non-trivial amounts; multiple regions have received more than EUR 10,000 per inhabitant since the 1990s. As figure **??** in the Appendix shows, the annual volume of the funds has increased over time. In the 1990s, funds accounted for 2-3 percent of local GDP in the regions with the largest receipts. In the 2010s, many regions receive EU funds worth more than 5 percent of local GDP.

The total economic size of the policy we consider is substantially larger than some of the policies that are considered in the related literature on place-based policies. The policy that Criscuolo et al. (2019) analyze, for instance, has a size of "about £164 million per year" (p. 57). Expenditure for the policy examined by Kline and Moretti (2014*a*) totals USD 20 billion over a period of 66 years. In terms of per capita amounts, however, EU funds are very similar to these policies. Plants in eligible areas in Criscuolo et al. (2019: 62) received yearly subsidies worth about £160 per worker and the policy studied by Kline and Moretti (2014*a*: 282) transferred USD 150 to the average resident in times of peak transfers. Similarly, EU funds to eligible regions amount to yearly per capita disbursements between 100 and 200 euros in most years.

[16] https://ec.europa.eu/regional_policy/en/funding/financial-management/

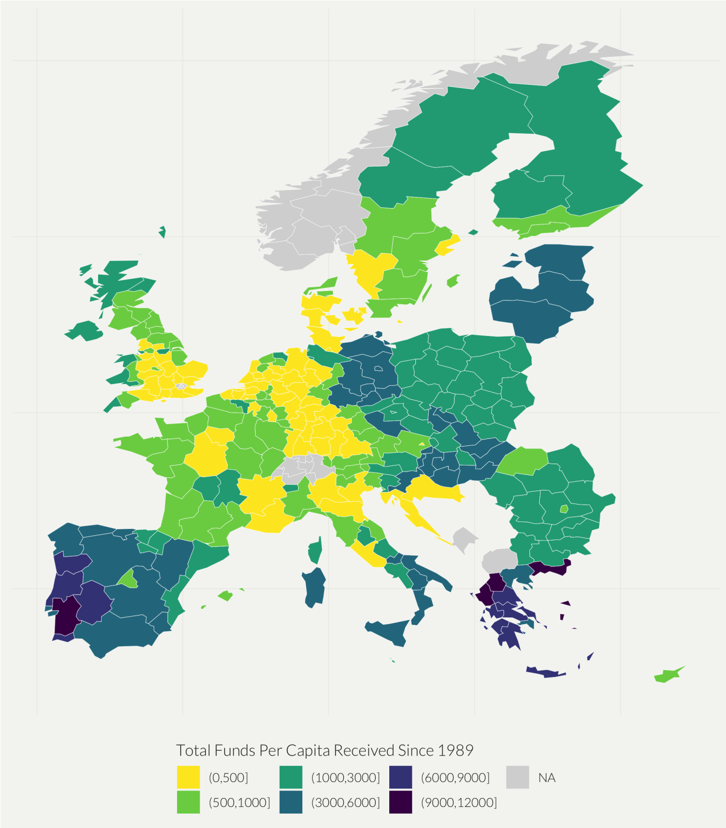
[17] In addition to the ERDF and the ESF, the EU's structural and investment funds include the Cohesion Fund (CF), the European Agricultural Fund for Rural Development (EAFRD), and the European Maritime and Fisheries Fund (EMFF). They are, however, smaller in volume and their allocation follows different rules.

[18] https://ec.europa.eu/regional_policy/en/funding/erdf/

[19] https://ec.europa.eu/regional_policy/en/funding/social-fund/

[20] https://cohesiondata.ec.europa.eu/stories/s/47md-x4nq

Figure 4: Disbursements of EU Funds Across Regions



Notes: The map plots the total amount of EU funds per capita that regions received between 1989 and 2017.

3.1 Identification I: Regression Discontinuity Design

We are interested in the effect of EU funds on income growth (Δy) for different deciles d of the regional income distribution within regions r:

$$\Delta y_{rtd} = \alpha + \beta_d funds_{rt} + \varepsilon_{drt}, \quad \forall\, d \in D, \tag{1}$$

where t indexes years.

A natural expectation is that EU funds are not allocated independently of regional income growth. As the stated goal of EU structural funds is to promote the cross-regional convergence of incomes it is plausible that regions with weaker growth prospects are more likely to receive a larger amount of funding. Hence, naive estimates of β would be biased downwards. It is, however, also plausible that policymakers have an incentive to allocate more funds to regions with better growth prospects in order to demonstrate the effectiveness of these funds. In this case, estimates of β that do not take endogenous allocation into account would be biased upwards. In sum, there are several reasons to expect an endogenous relationship:

$$\mathbb{E}(funds_{rt}, \varepsilon_{drt}) \neq 0 \tag{2}$$

To take potentially endogenous allocation of EU funds into account we rely on a discontinuity in the allocation of EU funds across regions. Although allocation rules in the observation period (1989-2017) changed, one feature was part of all agreements of the five programming periods that we consider: Regions with a GDP per capita below 75 percent of the respective EU average qualified for a substantially larger amount of EU funds than the remaining regions.

More specifically, the EU determines a region's eligibility for EU structural funds at the NUTS2-level. Across all funding periods, the largest per capita amounts of the ERDF and the ESF go to NUTS2-regions with a GDP per capita that is below 75 percent of the EU average. Over time, these regions were labelled as regions belonging to "Objective 1" (1989-2006 period), the "Convergence Objective" (2007-2013 period), or to the set of "less-developed regions" (2014-2020 period). While labelling varied over time, the rule that regions with a GDP below 75 percent of the community average receive the largest per capita amounts has remained in place from 1989 onward until the time of writing.

This allocation rule allows us to implement a regression discontinuity (RD) design. Our approach is similar to previous research that also relied on this discontinuity (e.g., Becker, Egger, and von Ehrlich 2010, 2019) but somewhat distinct along several dimensions.

First, we follow existing research in using a region's eligibility status as the treatment variable in the baseline but we extend this by using newly available data to define the treatment as the actual amount of disbursed flows to a given region. *Funds* is measured as yearly disbursements of ERDF and ESF funds to region *r* in year *t* as a share of regional GDP. The approach of using data on disbursements of EU funds stands in contrast to much of the previous work on the effects of EU regional policy, for which such data was not available. Most contributions to this literature use data on a region's formal eligibility for EU funds rather than data on actual fund disbursements (Eposti 2007; Becker, Egger, and von Ehrlich 2010, 2013, 2019). As the data show, the amounts of disbursed funds differ across regions with the same eligibility status (see Figure 4 and Figure 8). Data on actual disbursements, thus, add valuable information on the intensity of the treatment and compliance with the ”intention to treat.” [21]

Second, any RD design requires exact information on the forcing variable. However, the original data on regional GDP that the European Commission used to determine eligibility at the time was so far not available to existing research. Instead, scholars have used more recent GDP data from other sources to reconstruct the historical forcing variable.[22] Because of data revisions and differences in methodologies, however, the series differ, which leads to an incorrect mapping from the forcing variable to the treatment assignment. As a result, scholars find imperfect compliance with the institutional 75-% rule and resort to fuzzy RD methods.[23] Through correspondence with the European Commission's Directorate-General for Regional and Urban Policy (DG REGIO), we were able to recover the original data that were used for the historical decisions on eligibility. As a result, our data – visualized in Figure 7 below – points to almost perfect compliance with the institutional rule.[24] This allows us to also use sharp RD methods and produces more reliable estimates of the treatment effect at the cutoff.

Third, advances in the methodological literature on RD designs suggest that non-parametric estimations via local linear regressions are advantageous over parametric estimations in the full sample. For instance, Gelman and Imbens (2019) show that parametric approaches with high-order polynomials can produce noisy estimates. Calonico et al. (2017) and Calonico, Cattaneo, and Titiunik (2014) have proposed a non-parametric approach that estimates local linear models with robust bias-corrected confidence intervals. The recent literature recommends this *local* RD approach (see, e.g., Cunningham 2021) over the *global* approach that the existing literature on EU funds implements (see, e.g. Becker, Egger, and von Ehrlich 2019; Borin, Macchi, and Mancini 2021). We follow these recommendations and implement the approach proposed by Calonico, Cattaneo, and Titiunik (2014)

[21] Several other existing studies have used data on EU funds but were restricted by a more limited temporal and spatial data coverage and by missing crucial information on the timing of the disbursement (Dall'Erba and Fang 2017). Most EU payments are reimbursements and are thus usually made *after* the actual expenditure took place. Studies like ours that are interested in the immediate economic effects of these expenditures would be distorted if they considered the timing of the reimbursements rather than the timing of the expenditure. Information on the latter, however, was so far not available. The new data we use include information on the timing of the expenditure, allowing us to estimate the economic effects of actual expenditures.

[22] Scholars have typically used data from Cambridge Econometrics (Becker, Egger, and von Ehrlich 2013).

[23] See, for instance, Figure 1 in Becker, Egger, and von Ehrlich (2019).

[24] There are 15 remaining non-compliers. These result from exceptions for special regions like islands and from the fact that, in the early funding periods, the EU granted eligibility to some regions that surpassed the threshold only marginally. We discuss these exceptions and how we treat them below and in Table SI 1 in the Appendix.

via the RDROBUST package (Calonico et al. 2017).

Estimation. Based on theses considerations, we estimate variations of the following RD model:

$$\Delta y_{rtd} = \beta_d a_{rt} + \gamma f(gdp_{rt}^{EU}) + \mu_c + \tau_t + \epsilon_{rt}, \quad \forall d \in D \tag{3}$$

where $a_{rt} = 1_{(gdp_{rt}^{EU} > 75)}$ indicates observations above the eligibility cutoff. The function $f(.)$ includes local linear polynomials of gdp_{rt}^{EU} with different slopes above and below the cutoff. The sample for the local linear regressions is restricted to observations that satisfy $\mid gdp_{rt}^{EU} - 75 \mid < h$, where h is the RD bandwidth. Weights are based on a triangular kernel such that observations closer to the cutoff receive more weight. NUTS2 regions r are clustered in countries c, such that μ_c are country fixed effects. τ_t are year fixed effects. D is the set of the 10 deciles d of the intra-regional income distribution. In the RD logic, controlling for local polynomials of gdp_{EU}^{rt} in these regressions ensures that the estimates of β_d only capture the exogenous variation resulting from the discontinuity at the cutoff. Under standard RD assumptions, the sharp RD identifies the intention to treat (ITT) at the cutoff.

In addition to estimating the sharp RD model specified in equation 3, we also estimate fuzzy RD models, where a_{rt} is used in a first-stage regression to instrument a treatment variable T. Other than that the fuzzy RD specifications follow the sharp RD specification in equation 3:

$$\Delta y_{rtd} = \beta_d \widehat{T}_{rt} + \lambda f(gdp_{rt}^{EU}) + \mu_c + \tau_t + \epsilon_{rt}, \quad \forall d \in D \tag{4}$$

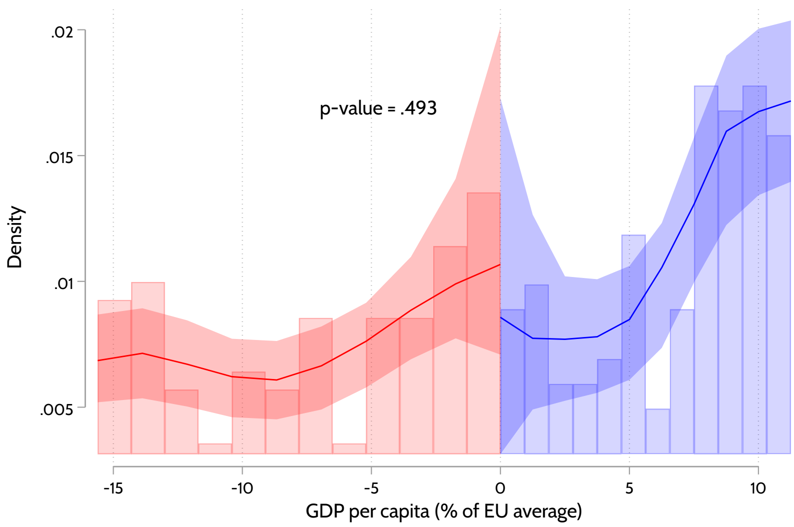
Here, T is either defined as the binary treatment variable *eligible*, or the continuous treatment variable *funds*. Regions are coded as *eligible* if they are classified as belonging to “Objective 1”, “Convergence Objective”, or to “less-developed regions” in the official EU documents and thus qualify for the largest volumes of EU funds (see Figure SI 7 for a map). The continuous variable *funds* is defined as yearly disbursements of EU funds as a share of regional GDP (see Figure SI 8 for a map).

The fuzzy RD identifies the local average treatment effect (LATE) of either the eligibility status or the amount of received EU funds at the cutoff.

3.2 Threats to Identification: RDD

The validity of this research design rests on two key assumptions. First, an immediate threat is the possibility that NUTS2-regions select themselves into EU funding (sorting). Previous research has extensively argued and shown that this is not the case (Becker, Egger, and von Ehrlich 2010, 2012, 2013). NUTS2-regions are unlikely to be capable to influence their GDP to the degree that they can reliably sort themselves just below the 75% EU average. Also, misreporting of GDP figures is unlikely to occur within the democratic settings of EU member states. Furthermore, we can directly test whether there are significant discontinuities in the density of observations around the cutoff with the help of local polynomial density estimation Cattaneo, Jansson, and Ma (2020). We plot the result of this test in Figure 5. As is visible, there is no statistically significant jump around the 75% cutoff. This adds further support to the assumption that sorting is unlikely to occur in the setting we study here.

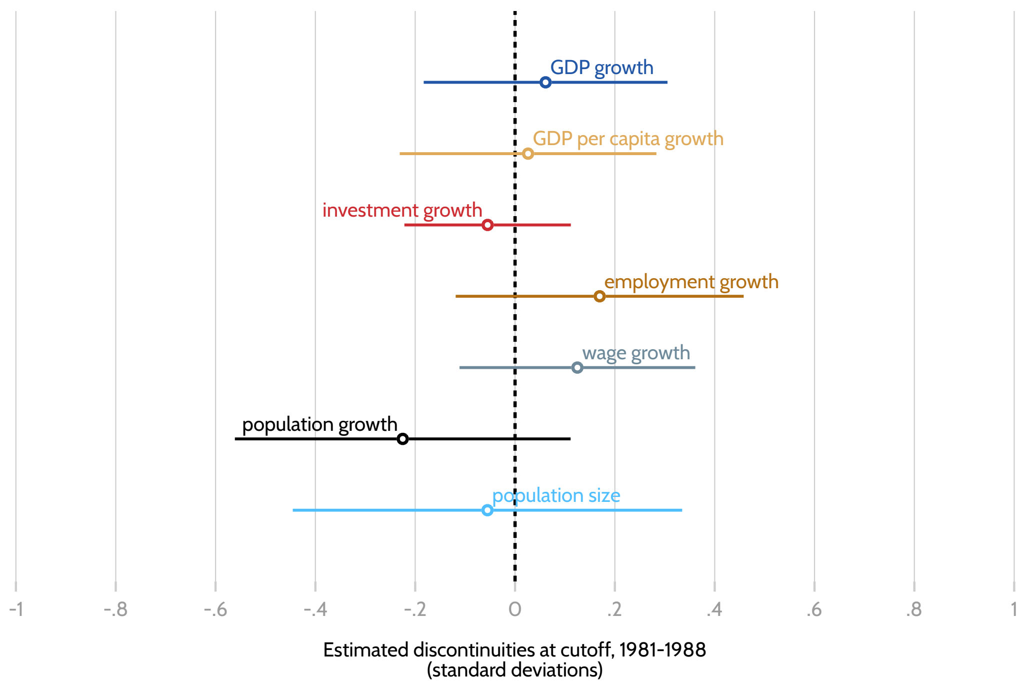
Figure 5: Manipulation test



Notes: The manipulation test is based on a local polynomial density estimation implemented with the RDDENSITY package by Cattaneo, Jansson, and Ma (2020). The test yields an estimate of -0.69 for the discontinuity of the density function at the threshold and fails to reject the null hypothesis of no discontinuity with a *p*-value of 0.49 (jackknifed robust standard errors).

Second, the research design assumes continuity around the threshold for other variables that could potentially affect the outcomes of interest. To test this, we conduct placebo tests in the pre-treatment period before the policy became active in 1989. We estimate the same model as in the baseline for the 1981-1988 period to test whether there are pre-treatment discontinuities in key economic variables at the 75%-threshold. We test this for the main economic outcomes that are available for this period from Cambridge Econometrics: GDP growth, GDP per capita growth, investment growth, employment growth, wage growth, population growth, and population size. If the treatment is truly locally randomized, there should not be any significant discontinuities in these variables at the threshold in the period before the policy becomes active. In Figure 6 we report the results of these seven placebo tests. The seven outcome variables are z-score standardized such that estimated coefficients indicate the size of the discontinuity in standard deviations. Reassuringly, we do not find any differences in pre-treatment characteristics. All coefficients are not statistically significant at conventional levels. Prior to the 1989 start of the place-based policy that uses the 75% threshold to determine eligibility, there is no discontinuity in key economic variables at this value.

Figure 6: Placebo test for pre-treatment period, 1981-1988



Notes: Reported are coefficients and 95% confidence intervals from seven sharp RD models. The models mirror the baseline specification (see equation 3 and Table 1) but use pre-treatment variables as outcomes. We use all data points available from the period *before* the EU cohesion policy became active (1981-1988). As in the baseline, the RD forcing variable is regional GDP per capita relative to the EU average and the (placebo) cutoff is set at 75%.

4 Main Results

This section presents the main results of estimating the effect of the place-based policy on incomes and their distribution within regions by means of the RD design described in the previous section.

4.1 First Stage: The 75%-Rule

We begin by examining the compliance of the place-based policy with the institutional rule that the RD design is based on. This constitutes the first stage of the main analysis.

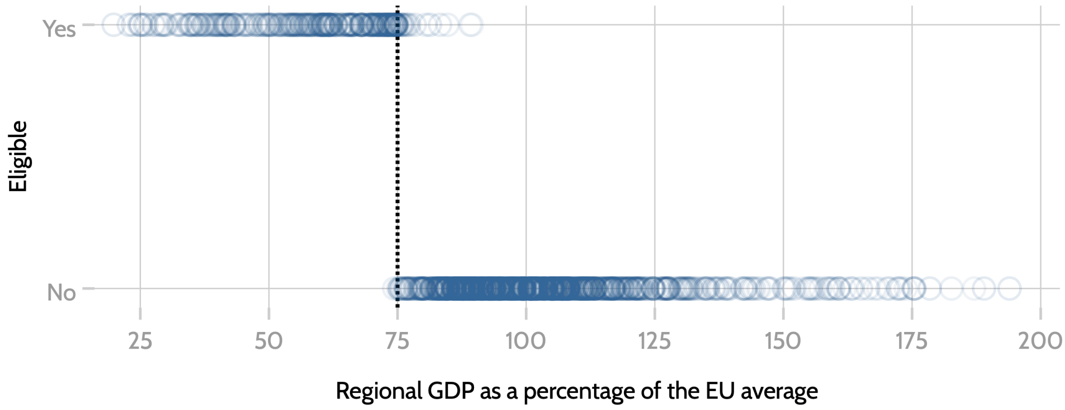
Figure 7 plots each region's official eligibility status against the forcing variable, GDP per capita as a percentage of the EU average. As is visible, compliance is almost perfect. In total, we observe non-compliance for 15 region-period observations. These result from exceptions for remote regions and from the fact that in the two first funding periods, the EU granted eligibility status to regions that were close to the cutoff in special cases.[25] We deal with these violations of the assignment rule in various ways. In the baseline analysis, we include all regions and estimate fuzzy RD regressions to account for imperfect compliance. In robustness regressions, we a) exclude all non-compliers (Table SI 4 and b) estimate a "donut" RDD, which excludes all observations close to the cutoff. All these approaches yield the same results mainly because there are so few exceptions and because, overall, the compliance with the institutional rule is strong.

Next, Figure 8 plots the actual disbursements that a region receives in a given year as a function of the forcing variable. Here, compliance is more fuzzy. It is clearly visible that regions above the 75%-cutoff receive less funding than those below the cutoff, but disbursements do not drop to zero above the cutoff. The disbursements to regions above the cutoff result from various reasons. a) According to the EU's rules, eligibility for the funds is reduced to a smaller share of the budget rather than to zero. b) There are delayed payments for regions that recently lost eligibility status. c) The EU implemented several exceptional rules and transition funds for regions that lost their eligibility status.[26] d) There are disbursements to the 15 exceptionally eligible regions discussed

[25] In the 1989-1999 period, the official regulations explicitly allow for the possibility to include "regions whose per capita GDP is close to that of the regions referred to in the first subparagraph [i.e., those below 75% of the EU average] and which have to be included within the scope of Objective 1 for special reasons." In Table SI 1 in the Appendix, we describe these exceptional cases one by one.

[26] One example is the decision to provide a reduced amount of funds to regions that lost eligibility only because of the EU Eastern enlargement in 2004 and 2007 (see section 6).

Figure 7: Eligibility for EU funds and the 75-percent rule



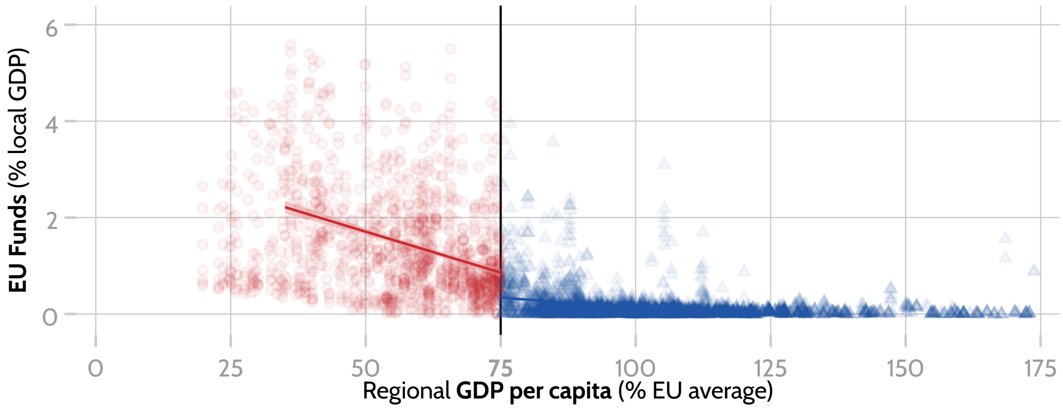
Notes: The figure plots each region's official eligibility status on the y-axis against its GDP per capita as a percentage of the EU average, i.e. the RD forcing variable, on the x-axis.

above. Nevertheless, the drop in funding volumes at the cutoff is tremendous.

We estimate the size of this drop in disbursements at the cutoff with the help of the local linear regressions, specified in equation 3 and plot results in Figure 9. The size and statistical significance of the estimated drop depends on the RD bandwidth. The strongest drop is estimated when following the previous literature and estimating the discontinuity in the global sample. For very small bandwidths, the local linear regression estimate insignificant discontinuities. In these small bandwidths the sample is terribly underpowered and the number of non-compliant, exceptional cases is high relative to the sample used for these regressions. When allowing the sample to become somewhat larger, regular observations receive more weight. Overall, the drop is statistically significant for most bandwidths between the two extremes of either very small or global bandwidths. To make sure that there is a robust first-stage effect on actual disbursements in the sample that is used for the subsequent analysis, the baseline analysis is based on the moderate bandwidth of 40 while robustness tests also show results for all alternative bandwidths.

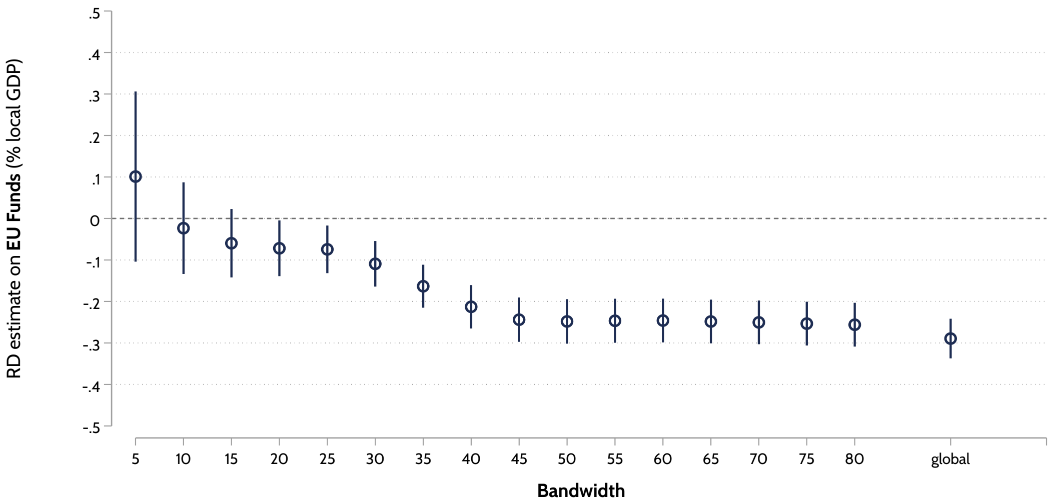
All in all, the analysis of the first-stage effect suggests that the place-based policy complies with the institutional rule used for the identification. The subsequent analysis of the policy's economic effects will use sharp RD methods to estimate the ITT of crossing the cutoff and fuzzy RD methods to estimate the LATE of eligibility as well as actual disbursements.

Figure 8: Disbursements of EU funds and the 75-percent rule: Raw data and local linear fits



Note: Plotted are raw data together with local linear fits below *(in red)* and above *(in blue)* the cutoff. The bandwidth used for estimating the local linear fits is 40. Linear fits are surrounded by 95% confidence intervals.

Figure 9: Disbursements of EU funds and the 75-percent rule: Local linear regressions



Notes: Local linear RD regressions based on equation 3, with EU funds as the outcome variable. 95% confidence intervals.

4.2 Economic Growth and Household Incomes

The analysis now turns to estimating the effect of EU funds on average regional income growth. Overall, there are economically substantial and statistically significant positive effects of the place-based policy in different measures of average incomes.

Table 1 initially examines effects on growth rates of regional GDP per capita from national accounts (column 1). The effect of crossing the 75%-cutoff from below – thus lowering the amount of funds the region is eligible to receive – is estimated to reduce annual regional growth by 0.35 percentage points.

The effect of eligibility estimated via the fuzzy RD in the bottom panel is an increase in growth by half a percentage point. Both effects are significant at the 1%-level. This result is similar to previous results in this literature even though the effect size is somewhat smaller.

Column 2 turns to our data on household incomes from household surveys. It uses as an outcome variable the annual growth rate of mean disposable household income at the regional level. The estimates from both the sharp RD and the fuzzy RD point to a substantially positive and statistically significant effect of EU funds on household incomes based on these micro-level data. The estimated effect size is remarkably similar to the estimates based on GDP data from national accounts. This is reassuring as it suggests that our newly collected data from household surveys captures a similar variation in incomes as GDP data from national accounts. This holds even though, the sample that can be used for the analyses based on household data is substantially smaller than the sample for the analyses based on national accounts data. The results also highlights that the regional increases in economic growth promoted by the policy translate into higher incomes at the level of households. In Appendices SI.5.1 and SI.5.2, we show that these result are robust to a wide range of alternative bandwidths and to RD regressions based on a uniform kernel instead of a triangular kernel.

Table 1: Income Growth

Intention-to-Treat Effect *(Sharp RD)*	(1) GDP per capita	(2) Household income
Above cutoff (75%)	-0.35	-0.30
	(0.09)	(0.14)
Country FE and Year FE	✓	✓
Observations	1267/3171	549/623
Local Average Treatment Effect *(Fuzzy RD)*	(1) GDP per capita	(2) Household income
Eligibility	0.49	0.40
	(0.11)	(0.15)
Country FE and Year FE	✓	✓
Observations	1266/3135	549/623

Notes: The table reports local linear RD estimates with robust nonparametric standard errors clustered at the NUTS2-level and reported in parentheses. The forcing variable is regional GDP per capita as a share of the EU average. The cutoff is at 75%. The bandwidth is 40. All estimations use a triangular kernel. The top panel reports results from sharp RD regressions. The bottom panel reports results from fuzzy RD regressions, with official eligibility status as the treatment.

4.3 Fiscal Multipliers Estimates

In order to better assess the size of this effect on the aggregate output of the local economy, we use this setting to estimate the local fiscal multiplier of the EU's public spending.

We follow standard notation in the related literature (e.g., Chodorow-Reich 2019; Kraay 2012) and define the spending multiplier of EU funds as the β^s in the following model of output growth as a function of public spending:

$$\frac{y_{rt} - y_{rt-1}}{y_{rt-1}} = \alpha + \beta^s \frac{funds_{rt}}{y_{rt-1}} + \epsilon_{rt} \tag{5}$$

We estimate this fiscal multiplier with our RD model and present the results in Table 2. All three specifications are fuzzy RD regressions with $\frac{funds_{rt}}{y_{rt-1}}$ as the continuous endogenous treatment variable. Specification 1 is a parametric fuzzy RD regression that is estimated by 2SLS in the global sample. Specification 2 is based on the same parametric model but is estimated as a local linear regression in the baseline bandwidth. Specification 3 implements a non-parametric bias-corrected RD regression in the same bandwidth.

All three estimates point to a fiscal multiplier close to 1. This suggests that the policy's redistribution of resources across European regions does neither increase nor decrease aggregate output in the European Union. This result aligns with the estimated ITTs in the previous section, where the discontinuity at the threshold is estimated to reduce funding by 0.2-0.3 pp of GDP and growth by 0.3-0.4 pp based on alternative specifications.

How does this effect size compare to the multipliers estimated in the related literature? Generally, our estimate is in line with recent empirical evidence on fiscal multipliers estimated in other settings and with other methods. The result supports the conclusion in Ramey (2011)'s review that "the bulk of estimates imply that the aggregate multiplier for a temporary rise in government purchases not accompanied by an increase in current distortionary taxes is probably between 0.8 and 1.5." When comparing the estimate to related work on cross-sectional fiscal spending multipliers, our point estimates are slightly smaller than the mean estimate of 1.7 in Chodorow-Reich (2019)'s review but our 95% confidence intervals also include this value. When comparing the result to earlier work on the EU Cohesion Policy, our estimates of the local fiscal multiplier support and are in line with Becker, Egger, and von Ehrlich (2010: p.589), who conclude that "every Euro spent on Objective 1 transfers leads to 1.20 EUR of additional GDP," based on different data, a different sample and a different estimation strategy.

Table 2: Fiscal Multiplier Estimates

	(1)	(2)	(3)
EU Funds (% GDP)	0.92	1.07	1.47
	(0.48)	(0.91)	(0.33)
Country FE and Year FE	✓	✓	✓
Estimation	parametric	parametric	non-parametric
Bandwidth	global	40	40
F-statistic (Kleibergen-Paap)	56.79	20.95	
First Stage:			
$1(GDP^{EU} > 75)$	-0.45	-0.28	-0.21
	(0.06)	(0.06)	(0.03)

Notes: RD estimates. Outcome variable: Growth of GDP per capita. If estimation is *parametric* results are from a 2SLS regression with linear polynomials of the forcing variable. If estimation is *non-parametric* results are local linear RD estimates with robust nonparametric standard errors estimated with a triangular kernel as in Table 1.

4.4 Inequality

Having provided evidence on the positive *aggregate* effects of EU funds on incomes, we now turn to answering this paper's main question: How are these income gains *distributed* within regions?

First, we use the household-level data to calculate different measures of income inequality within regions: the Gini coefficient, the P90/P10 ratio, the P80/P20 ratio, and the coefficient of variation (CV).[27]

To estimate how intra-regional inequality reacts to the EU's place-based policy we estimate the same models as for aggregate income growth and use year-on-year differences of these inequality measures as outcome variables. The results are reported in Table 3 and show that EU funds increase inequality within European regions. Eligibility for the policy increases the local Gini coefficient [0, 100] by about 0.18 points. This is equivalent to five percent of a standard deviation per year of eligibility ($\text{mean}_{\text{gini}} = 30.62$; $\text{sd}_{\text{gini}} = 3.68$). The ratio of household income of the 90$^{\text{th}}$ percentile relative to the

[27]These measures are all standard inequality measures but react differently to changes in different parts of the income distribution. The Gini coefficient is most sensitive to changes in the middle of the distribution, the percentile ratios mostly capture inequality between the top and the bottom, and the CV puts most weight on the right tail. All measures are positively correlated and indicate the inequality of disposable household income within regions.

10[th] percentile increases by 6.4 percentage points (9 percent of a standard deviation, $\text{mean}_{P90/P10} = 3.98$; $\text{sd}_{P90/P10} = 0.74$) and the effect size on the P80/P20 ratio is 2.4 percentage points (8 percent of a standard deviation, $\text{mean}_{P80/P20} = 2.44$; $\text{sd}_{P80/P20} = 0.30$). For the Gini coefficient and the two most common percentile ratios, the results are statistically significant at the one-percent level. The estimates on the coefficient of variation (CV) is also positive but not statistically significant at conventional levels. As before, the top panel of the table shows the intention to treat estimated by sharp RD while the bottom panel shows the LATE of eligibility estimated by fuzzy RD. Appendices SI.5.1 and SI.5.2, show that these result are robust to a wide range of alternative bandwidths and to RD regressions based on a uniform kernel instead of a triangular kernel.

In concert with the estimated growth effects, these results suggest that the place-based policy benefits the rich in supported regions more than it benefits the poor. We examine the mechanisms behind this effect in more detail in the next section and study distributional effects across income groups, factors of production, sectors, and skill levels.

Table 3: EU Funds and Inequality Within Regions

Intention to Treat *(Sharp RD)*				
	Gini Coefficient	P90/P10 ratio	P80/P20 ratio	Coefficient of Variation
Above cutoff (75%)	-0.141	-0.051	-0.019	-0.005
	(0.032)	(0.018)	(0.006)	(0.004)
Country FE and Year FE	✓	✓	✓	✓
Observations	575/657	550/644	550/644	547/644
Local Average Treatment Effect *(Fuzzy RD)*				
	Gini Coefficient	P90/P10 ratio	P80/P20 ratio	Coefficient of Variation
Eligibility	0.184	0.064	0.024	0.005
	(0.037)	(0.022)	(0.007)	(0.005)
Country FE and Year FE	✓	✓	✓	✓
Observations	575/657	550/644	550/644	547/644

Notes: RD estimates. Outcome variable: year-on-year differences of various inequality measures. Specifications as in Table 1. Standard errors clustered by NUTS 2 regions in parentheses.

5 Distributional Effects and Mechanisms

5.1 Distributional Effects Across Income Groups and Factors

To examine the mechanisms and distributional effects behind this increase in inequality, as a next step, we split each region into ten equally sized deciles based on the intra-regional distribution of disposable household income. For each decile in each region and each year we compute the growth rates of the most important income types. We differentiate between household income derived from *labor*, from *capital* and from public *transfers*.

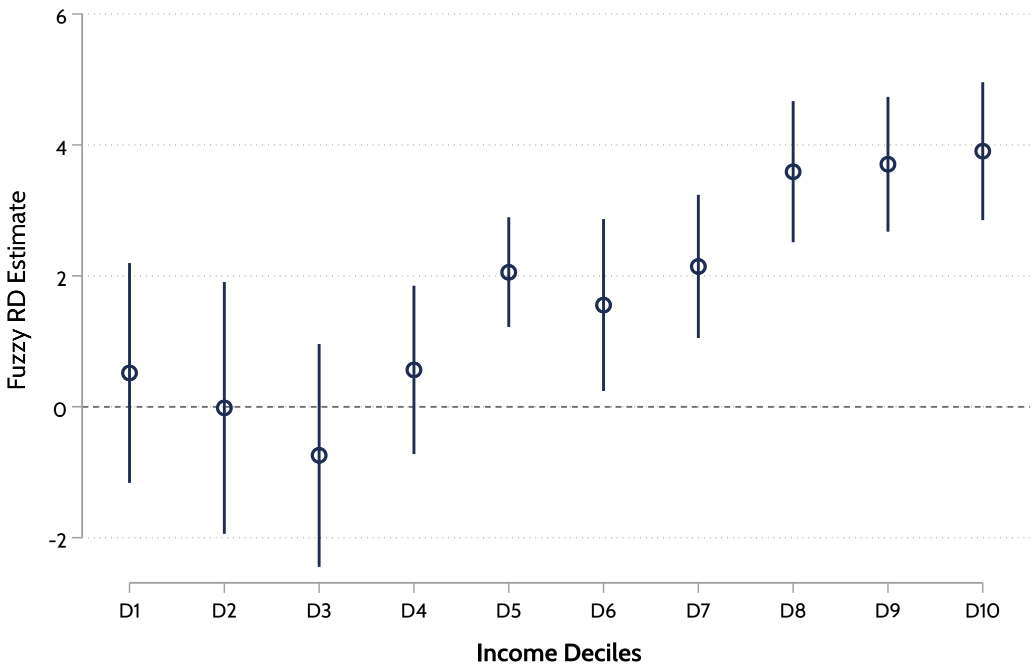
In models that follow the fuzzy RD specifications of the growth regressions in Table 1 above, we first estimate the effect of the place-based policy on the decile-specific growth of labor income. Figure 10 plots the results of these ten regressions as a coefficient plot. The results uncover a clear pattern. Increases in labor income are strong and statistically significant for households at the top of regional income distributions, but small and insignificant for those at the bottom. Eligibility for the place-based policy increases labor income growth of households in the top 30 percent of the regional income distribution by 3-4 percentage points. For the bottom 40 percent, effects are not distinguishable from zero at conventional levels of statistical significance. Households around the regional median (deciles 5-7) see increases in labor income by about 2 percentage points.

An alternative mechanism through which EU funds increase inequality could be that they disproportionally increase capital gains by rich capital owners.[28] When applying the analogous approach for income derived from capital, we do not find significant effects for any decile (Figure 12a). EU funds thus do not seem to increase local inequality by benefiting local capital owners more than local workers.

In addition to "factor income" derived from labor and capital, the third major source of income for the households we consider are public transfers. In principle, governments could use the funds to finance public transfers. While not intended for this purpose, the funds are fungible and governments might substitute their local investments by EU funds and use the newly available funds to increase transfers. When testing this hypothesis, the results for public transfers do not point so such an effect. Instead, nine of of ten coefficients are not statistically significant. While the statistically significant

[28] Alder, Shao, and Zilibotti (2016) find that special economic zones in China increased GDP mainly through a positive effect on physical capital accumulation.

Figure 10: Effects on labor income by regional decile



Notes: Fuzzy RD regressions. Outcome variable: Growth of labor income by region-decile. Specifications as in Table 1. Plotted are estimated effects of the treatment variable *eligibility* along with 95% confidence intervals.

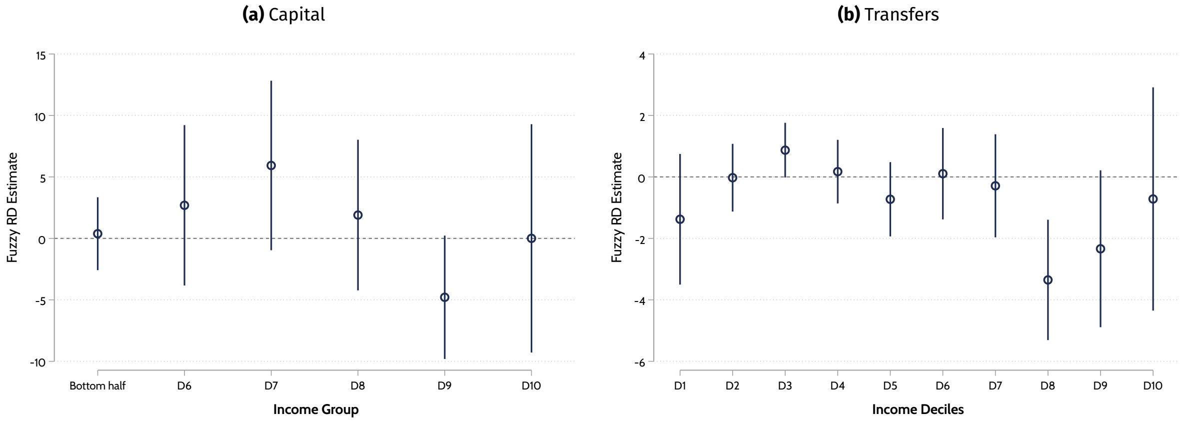
negative result for the 8th decile could indicate that growth of labor income reduced eligibility for public transfers in this income group, this could also be due to chance and the results do not point to a systematic pattern. EU funds do not seem to be used to finance public transfers.

In sum, these results suggest that EU Funds increase inequality by promoting the labor incomes of those at the upper end of regional income distributions. The labor income of the funded regions' least well-off is not affected.

The evidence on the distributional effects on labor and capital income shows that changes in the *factor* distribution of income do not explain the rise in inequality caused by EU funds. If differences in gains between capital and labor were driving the rise in inequality, the evidence would have to point to larger gains for (rich) capital owners than for (poor) workers. Instead, there are distributional effects within the factor labor that increase the wages of relatively rich workers more than those of poor workers.

To examine the mechanisms behind this further, we turn from the factor distribution of income gains to their sectoral distribution. Do EU funds benefit rich workers more than poor workers because they primarily reach workers in sectors with higher incomes?

Figure 11: Effects on income from capital and transfers by regional decile



Notes: Fuzzy RD regressions. Outcome variables: growth of capital gains **(a)** and income from public transfers **(b)** by region-decile. Specifications as in Table 1. For capital gains, the bottom half is combined as capital gains in this group are close to zero. Plotted are estimated effects of the treatment variable *eligibility* along with 95% confidence intervals.

5.2 Distributional Effects Across Sectors: Macro-level Evidence

Turning to macro data from national accounts, we initially examine the extent to which EU funds spur investments across economic sectors.[29] In Table 4, we employ our baseline sample and our baseline RD specification while using growth rates of local investment as outcome variables. Column 1 points to a statistically significant effect of EU funds on overall investment (gross fixed capital formation).

Table 4: Investments by Sector

	DV: Growth rate of investment by sector						
	all sectors	public sector	industrial sector	service sector	construction sector	financial sector	agricultural sector
Eligibility	1.48	5.07	3.08	2.77	8.01	0.91	1.43
	(0.35)	(0.50)	(1.30)	(1.21)	(1.91)	(0.56)	(0.58)
Country FE and Year FE	✓	✓	✓	✓	✓	✓	✓
Share in total investment	100	22	22	17	5	28	5
Mean wage	12704	18221	16915	11194	11569	13879	4343
Observations	989/2479	989/2479	989/2479	989/2479	989/2479	989/2479	989/2479

Notes: Fuzzy RD regressions. Outcome variables: yearly growth rates of regional investment across sectors (see top row). Specifications as in Table 1.

Next, we examine whether these investments, and the place-based policy more generally, translate into job creation in these sectors. Based on data from Eurostat, we calculate sector-specific employment rates per NUTS2-region and use year-to-year changes as outcome variables in the regressions reported in Table 5. Column 1 shows that EU funds lead to a significant increase in the

[29] See Liu (2019); Aghion et al. (2015) for research on why the effectiveness of industrial policy may differ across sectors.

overall employment rate. Each year of eligibility increases the average region's employment rate by about 0.17 percentage points. The remaining columns disaggregate employment rates by sector. The results document that the largest positive employment effects are found in the same sectors in which EU funds spur investments. There is statistically significant evidence for positive effects in the public, service, construction and financial sector. A negative effect on agricultural employment suggests that the policy contributes to the structural change from farm to nonfarm employment.

In sum, the place-based policy creates local jobs across a variety of sectors. While there is some evidence for a tendency of the policy to shift employment from the agricultural sector to other sectors, it does not systematically and exclusively promote employment in the highest-paying sectors.

Table 5: Jobs by Sector

	DV: Change in employment rate by sector						
	all sectors	public sector	industrial sector	service sector	construction sector	financial sector	agricultural sector
Eligibility	0.17	0.06	-0.00	0.05	0.05	0.05	-0.04
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Country FE and Year FE	✓	✓	✓	✓	✓	✓	✓
Share in total employment	100	26	18	26	8	8	14
Mean wage	12704	18221	16915	11194	11569	13879	4343
Observations	989/2479	989/2479	989/2479	989/2479	989/2479	989/2479	989/2479

Notes: Fuzzy RD regressions. Outcome variables: year-on-year differences of employment rates across sectors. Specifications as in Table 1.

Table SI 2 complements the analysis on employment rates with an analysis of the policy's effect on the unemployment rate. Irrespective of whether the overall rate, the long-term or the youth unemployment rate are considered the policy is estimated to significantly and substantially reduce local unemployment rates.

5.3 Distributional Effects Across Skill-Levels: Individual-level Evidence

In its attempt to explain the unequal effect of the place-based policy on rich and poor in supported regions, the analysis of mechanisms has so far focused on the distribution of income gains across factors and sectors. As gains are neither biased toward capital owners nor toward high-income sectors, we apply a third analytical distinction and examine heterogeneity by skill level. [30] We examine the

[30] In a sense, our approach of differentiating by production factors, sectors, and skill mirrors the variety of approaches in research on trade and inequality. Whereas earlier research focused on inequality across factors (à la Heckser-Ohlin (Stolper and Samuelson 1941)) and sectors (à la Ricardo-Viner), the recent literature emphasizes unequal effects of

hypothesis that the place-based policy benefits high-skilled workers more than low-skilled workers. There are several potential explanations for such a tendency. First, as it requires human resources to acquire information on and apply for the place-based funding, firms that employ high-skilled workers might be in a superior position to access the funds. Second, firms with high-skilled employees tend to be more productive. They might thus have an advantage to pay the costs associated with accessing the funds. Third, Bachtrögler et al. (2019) report that EU funds in less developed regions support relatively large projects and relatively large beneficiaries. (A motivating factor might be the reduction of the administrative burden for a small number of large projects relative to a large number of small projects.) If larger firms employ more high-skilled workers, the focus on large projects and beneficiaries can lead to a tendency of EU funds to benefit the better educated.

In order to test this mechanism, we require data on education at the level of the individual. We collect this information from the same national surveys that we used to generate measures of regional inequality in section 2 but now use the individual-level information rather than the household-level data that were used until here. These data include individual-level information on educational background, which we harmonize across national surveys. Based on these measures, we then classify individuals as low-skilled, medium-skilled or high-skilled. For each education group in each region and in each year, we then calculate the annual growth rate of the group's labor income. In order to not distort the measure by including individuals with different skill levels that are too young or too old to work, we only consider each region's working-age population for this exercise.

In Table 6, we use these education-specific growth rates of labor income as dependent variables. We find positive effects for all groups but the strongest effects are visible for the high-skilled individuals within regions. Funding eligibility increases the income growth of high-skilled workers by 3 percentage points. The effect on the labor incomes of low-skilled workers is estimated at 1.8 percentage points. Estimated effects on medium-skilled workers are in between, with an estimated coefficient of 2.6. As is visible in the bottom row of the table, average labor incomes of the highly educated are more than twice as large as those of the low educated.

In sum, these results offer an explanation for the unequal effects of the place-based policy. The income gains are strongest for high-skilled workers. As these have, on average, higher incomes than

trade across heterogeneous firms that differ in the skill-level of their employees (à la Melitz (2003)).

low-skilled workers, inequality within supported regions increases.

Table 6: The Role of Education: Individual-level Evidence

	DV: Growth of labor income by education level		
	Low Education	Medium Education	High Education
Eligibility	1.828	2.590	2.989
	(0.513)	(0.429)	(0.547)
Country FE and Year FE	✓	✓	✓
Observations	520/529	520/529	520/529
Mean income	11220	15586	24806

Notes: Fuzzy RD regressions. Outcome variables: growth of disposable household income by level of education per region and year. Specifications as in Table 1.

5.3.1 Probing the Mechanism with Data from Surveys among Recipients

To further probe this mechanism, we turn to an alternative empirical strategy with alternative data. Rather than estimating the effect of the policy on incomes, we rely on surveys that directly asked respondents in supported regions whether they personally benefited from the policy. The data come from Borz, Brandenburg, and Mendez (2022) who asked 8,559 respondents in 17 European regions (the samples includes a minimum of 500 respondents per region).[31] On the one hand, the survey includes regions below the 75%-thresholds that receive a large amount of funds. An example is the Hungarian region of Nyugat-Dunantul, where more than EUR 3000 per capita were spent in the 2007-2013 funding period. On the other hand, the survey also includes relatively rich European regions like the German region of Baden-Wuerttemberg where only EUR 18 per capita were spent in the same period. In addition to asking respondents whether they personally benefitted from the funds, the survey also collected information on socio-economic characteristics of respondents and on respondents' knowledge of and attitudes toward EU policies.

In Table , we use these data in simple OLS regressions, where the outcome variable is a binary indicator for respondents who state that they personally benefited from the policy. Columns 1 shows that individuals with higher incomes are more likely to respond affirmatively. The same is true for respondents in regions that received more EU funds, that are younger, and that are employed in the agricultural sector. We control for the latter to make sure that the result is not driven by personal

[31]These regions are: Cyprus, Kentriki Makedonia, Baden-Wuerttemberg, Thueringen, Nyugat-Dunantul, Southern and Eastern Ireland, Lombardia, Podkarpackie, Pomorskie, Vest, Zahodna Slovenija, Castilla y Leon, Andalucia, Flevoland, Limburg, Scotland, and North East England.

benefits from the EU's agricultural subsidies. Results remain virtually unchanged when region fixed effects are added (column 2). Column 3 adds an interaction to test whether the association between income and reported benefits depends on the volume of funds that the respondent's home region receives. In line with expectations, the association is stronger in regions that receive more funds. (Figure SI 18 in the Appendix shows the marginal effects plot for this regression.) While we cannot interpret these results as causal evidence, these results align with the main finding that richer individuals are more likely to benefit from the policy.

Guided by the results on the mechanism, columns 4-6 repeat the same analysis with education as the explanatory variable. Again, the results fit to our previous findings. More highly-educated individuals are more likely to report that they personally benefited from the policy. This association is stronger in regions that receive more funds.

Arguably, this result could be driven by a better understanding and knowledge of the policy among the better-educated. To mitigate the concern, column 7 includes both income and education as explanatory variables. The positive associations remain statistically significant. Table SI 7 in the Appendix goes one step further and additionally controls for variables that indicate whether respondents report that they *know about the policy*. With these controls, the size of the coefficients declines somewhat but the associations retain the statistical and economic significance. The result that richer and better-educated individuals are more likely to report personal benefits from the policy is not only driven by the fact that these respondents have a better knowledge of the policy.

5.4 Alternative Mechanisms

5.4.1 Spatial Distribution within Regions: Rural and Urban Areas

In Table SI 3, we examine whether the spatial distribution of funds within regions could explain the inequality-increasing effects. To do so, we differentiate between households in rural and urban areas. As the last row in Table SI 3 shows, urban areas are richer by about 10 percent. If the place-based funds would be biased to urban areas, this could explain the larger income gains for richer households. If anything, however, the results point in the opposite direction. Income gains from place-based funds are slightly larger in more rural areas. The unequal spatial distribution of funds within regions thus does not explain the policy's inequality-increasing effects.

Table 7: Self-reported Personal Benefit: Survey Evidence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Income	0.020	0.020	0.001				0.012
	(0.007)	(0.006)	(0.004)				(0.006)
Income × EU funds (% GDP)			0.020				
			(0.003)				
Education				0.041	0.038	0.031	0.037
				(0.005)	(0.003)	(0.004)	(0.003)
Education × EU funds (% GDP)						0.008	
						(0.004)	
EU funds (% GDP)	0.033			0.031			
	(0.021)			(0.018)			
Age	-0.001	-0.001	-0.001	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Agricultural Sector	0.015	0.023	0.024	0.048	0.051	0.054	0.052
	(0.026)	(0.022)	(0.022)	(0.027)	(0.024)	(0.023)	(0.023)
Region FE		✓	✓		✓	✓	✓
Regions	17	17	17	17	17	17	17
Observations	8559	8559	8559	8559	8559	8559	8559

Notes: OLS regressions. Outcome variable: Binary indicator for respondents who state that they "personally benefited" from a project funded by EU Funds. Standard errors clustered by NUTS 2 regions in parentheses.

5.4.2 Rents

As a final mechanism, we also look at the effects of EU Funds on housing costs. In theory, place-based financial support could lead to increasing rents if local housing supply is inelastic. The funds may thus increase household incomes without increasing household utility because income gains are absorbed by landlords via rising rents; and landlords may live in other regions. In SI 9, we thus examine effects on household expenditure on housing costs but fail to find significant effects for any income decile. As all surveys that we consider also include data on *housing costs*, we can also test the hypothesis that place-based funding increases local rents.

6 The Temporal Dimension: DiD evidence

6.1 Empirical Setting and Identification II: DiD

Having studied the effects of the place-based policy through the lenses of an RD design, we relied mainly on spatial variation. To better understand the temporal dimension of these effects, the subsequent section extends our results in a different setting and with an alternative identification strategy. This analysis focuses on an episode where multiple regions lost access to a large share of place-based funding. It thus shows how aggregate and distributional outcomes react when place-based funding ends.

This question is relevant from both a scientific and from a policy perspective. First, it is unclear whether the effects of an increase in place-based funding are symmetric to the effects of a decrease. Moreover, it is not obvious when any effects of a reduction of place-based funding will materialize. Are effects immediate or lagged? Are there anticipation effects? For policy makers the question is important as place-based policies are typically intended as a form of temporary support that ends when the policy goal of catching up is achieved. Evidence on economic performance at times when place-based funding ends may thus support the design of policies that minimize the potentially adverse effects of stopping place-based transfers.

Our empirical analysis focuses on the transition of EU funding periods between 2006 and 2007. When the 2000-2006 funding period ended, more regions than usual dropped out of the category of the most heavily funded regions. This was because in 2006 there were two reasons for losing this eligibility. One simple reason was the fact that multiple funded regions had grown fast and had surpassed the relevant threshold with GDP-per-capita values larger than 75% of the EU average. The second reason was the EU Eastern enlargement. In 2004 and 2007, new member states with lower average incomes joined the Union. As a result, the EU average GDP per capita fell. For the original members, this meant that their GDP-per-capita level *increased relative to the EU average without increasing in absolute terms*. At the same time, the 75% rule remained in place. As a result, several regions which had been eligible in the 2000-2006 funding periods became ineligible in the 2007-2013 funding period even though they would have remained below the 75% threshold had the EU not been enlarged. These regions – so-called ”phasing out” regions – lost access to the place-based policy for a reason that is unrelated to the economic development of these regions themselves.

To reduce the disadvantage that this meant for these regions, the EU granted these regions so-called ”phasing-out” support; a limited amount of place-based funding for the 2007-2013 period. The volumes of this transitory support, however, were substantially smaller than what they would have received as fully eligible regions. We provide evidence on this below.

To estimate the consequences of losing access to the place-based policy, we study the regions that lost eligibility in 2006/7 and compare them to the regions that remained eligible. This analysis places a particular emphasis on the "phasing-out" regions as their loss of eligibility status is exogenous to economic developments in the regions. We conduct this analysis based on variations of the following difference-in-differences model:

$$y_{rt} = \alpha_r + \tau_t + \beta(D_r \times \textit{Post}_t) + \varepsilon_{rt} \tag{6}$$

where *D* indicates, depending on the specification, either the "phasing-out regions", regular dropout regions, or all 2007 dropout regions. The estimand of interest is β indicating the effect of dropping out from funding after 2006 on measures of income levels and income inequality (y_{rt}); α_r and τ_t are region and year fixed effects respectively, ε_{rt} the error term. As before, we cluster our standard errors at the regional level. The sample is restricted to the 2000-2013 period – i.e. the two funding periods 2000-2006 and 2007-2013 – and to regions that were eligible in the 2000-2006 funding period.

Then, to better identify the timing of the effects, we allow the DiD estimate to vary by year and estimate the following event-study specification:

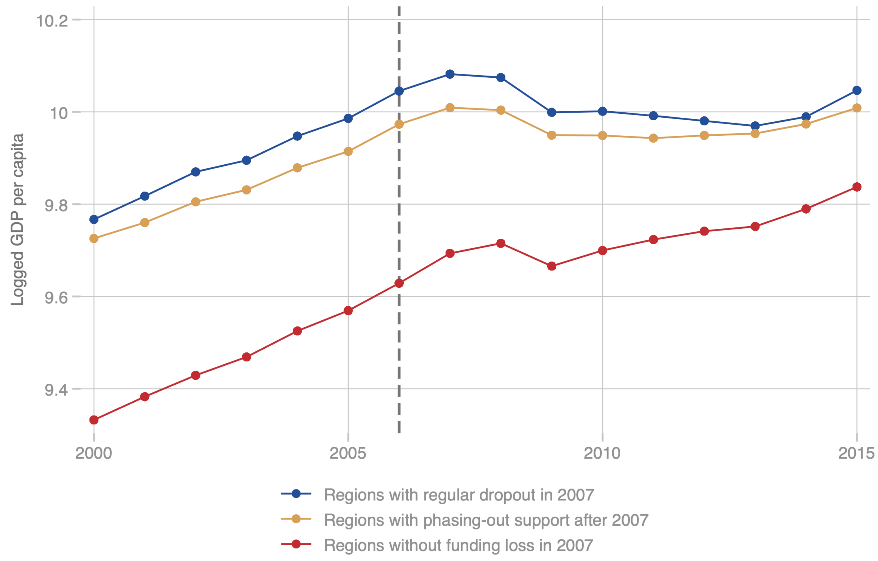
$$y_{rt} = \alpha_r + \tau_t + \sum_{t=2000}^{2013} \beta_t(\mathsf{D}_r \times \tau_t) + \varepsilon_{rt} \tag{7}$$

In this model, the dropout region indicator *D* is interacted with year fixed effects (τ). This allows us to examine pre-trends and determine the years after treatment that drive the average effect.

6.2 Parallel Trends: Descriptive Evidence

Before turning to the results of the DiD estimation, we discuss the key threats to identification. As with the previously discussed RD approach, sorting and compound treatment could constitute a potential threat to identification. Yet, as we have established above when discussing the RD design both threats do not apply to this setting. The major assumption in the DiD design is the parallel trends assumption. To consider our estimate of β as unbiased, we have to assume that the dropout regions would have followed the same trend in outcomes as the control regions that remained eligible after 2006, if they had not dropped out. While this assumption is untestable, we can examine trends in outcomes prior to the treatment.

Figure 13: Trends in GDP per capita before and after 2007



Notes: The figure plots unweighted averages of logged GDP per capita across the different types of regions. The dashed vertical line indicates 2006, the last year in which the regions had the same eligibility status.

Figure 13 plots the average GDP per capita before and after the treatment at the end of 2006 across the three groups of regions (regular dropout, phasing-out support, no funding loss). Differences in GDP per capita levels before the treatment are as expected: Regions that will dropout regularly are substantially richer than regions that will remain eligible and somewhat richer than regions that will receive phasing-out support after 2006. More importantly, all three groups are on a parallel growth path before 2006. The absence of differences in pre-treatment trends enhances the plausibility of the assumption that trends would have remained parallel without the treatment. After the treatment, however, trends stop being parallel. Regions that remain eligible grow faster than regions that stopped being eligible. Phasing-out regions with limited transitory support grow faster than ineligible regions but more slowly than regions will full access. While these trends enhance the plausibility of the identifying assumption and give a first indication of the effect of losing access to EU funds, we turn to a more rigorous, regression-based approach in the following.

6.3 Results: DiD

6.3.1 Two-period DiD

Table 8 reports the results from estimating the DiD model in equation 6. Panel A of this table shows the estimates for the amount of funding that was lost by regions that lost their eligibility status in 2007; the outcome variable is *EU funds* as a share of local GDP. Column 1 compares *phasing-out regions* to the regions that remained eligible after 2007. The results show that these regions lost annual EU funds worth about 1.4 percent of their local GDP after 2007. Columns 2 reports the analogous result for the all *regular-dropout regions*, who did not receive the transitory compensation for their loss of eligibility due to the EU's enlargement. The estimated amount of annual funding that these regions lost is estimated to be only marginally larger 1.5. Column 3 reports the result for all regions that lost eligibility without differentiating between the two groups.

Panel B then examines the effect of the dropouts on economic growth. We find substantially negative effects across the three specifications, which are analogous to those reported in Panel A with *annual growth of GDP per capita* as the outcome. After losing eligibility, *phasing-out regions* grow by about 1.6 percentage points less per year than regions that remained eligible. This is a sizeable effect that corresponds to about 30% of a standard deviation of the growth rate in this sample. In concert with the estimate that the treated regions lose EU funds worth about 1.4 percent of their local GDP, this points to a fiscal multiplier of 1.1. This DiD estimate closely matches the RD estimate of the fiscal multiplier. The estimated reduction in the growth rate for regions that regularly lost access to the place-based policy without receiving phasing-out support is somewhat larger (-3.3). The average effect for all dropout regions is estimated to lie between the two (-2.4).

Panel C turns to the distributional effects of losing access to the place-based policy. We find an inequality-reducing effect on *phasing-out regions*. Model 7 estimates a decrease in the Gini coefficient by 1.7 points (40% of a standard deviation in this sample). This finding is consistent with the RD result that the place-based policy increases income inequality. The estimate for *regular-dropout regions* is also negative but not statistically significant at conventional levels. This latter result could either indicate an absence of a treatment effect in this group but could also be due to an endogeneity bias resulting from the fact that these regions lost access to the place-based policy because of economic developments in the regions.

Table 8: When Place-based Funding Ends: DiD Evidence

Panel A: EU funds (% GDP)			
	(1)	(2)	(3)
Phasing-out regions × Post	-1.44		
	(0.14)		
Regular-dropout regions × Post		-1.50	
		(0.20)	
All dropout regions × Post			-1.47
			(0.15)
Observations	1081	1066	1234
Panel B: GDP per capita growth			
	(4)	(5)	(6)
Phasing-out regions × Post	-1.63		
	(0.91)		
Regular-dropout regions × Post		-3.33	
		(0.71)	
All dropout regions × Post			-2.44
			(0.67)
Observations	1090	1074	1242
Panel C: Gini coefficient			
	(7)	(8)	(9)
Phasing-out regions × Post	-1.75		
	(0.67)		
Regular-dropout regions × Post		-0.78	
		(0.73)	
All dropout regions × Post			-1.15
			(0.60)
Observations	525	552	594
Region FE	✓	✓	✓
Year FE	✓	✓	✓
Control regions	still eligible	still eligible	still eligible

Notes: Two-way fixed-effects regressions estimated by OLS (see equation 6). Outcome variables are indicated in bold. The sample is restricted to the 2000-2013 period and to regions that were eligible in the 2000-2006 funding period. Control regions are all regions that remained fully eligible in the 2007-2013 funding period. Standard errors clustered by NUTS 2 regions are reported in parentheses.

6.3.2 Event Study

Having studied the average effects of the loss of place-based funding we turn to the year-specific effects estimated based on the event-study design. Figure 14 plots the results of estimating equation 7 for *phasing-out* regions.[32] Initially, panel A shows the change in place-based funding that regions received before and after the treatment. It becomes visible that funding volumes in the regions that lost access were largest between 2001 and 2003. The most substantial drop in funding volumes is

[32] Analogous results for regular-dropout regions and all dropout regions are reported in the Appendix.

visible between 2008 and 2010.

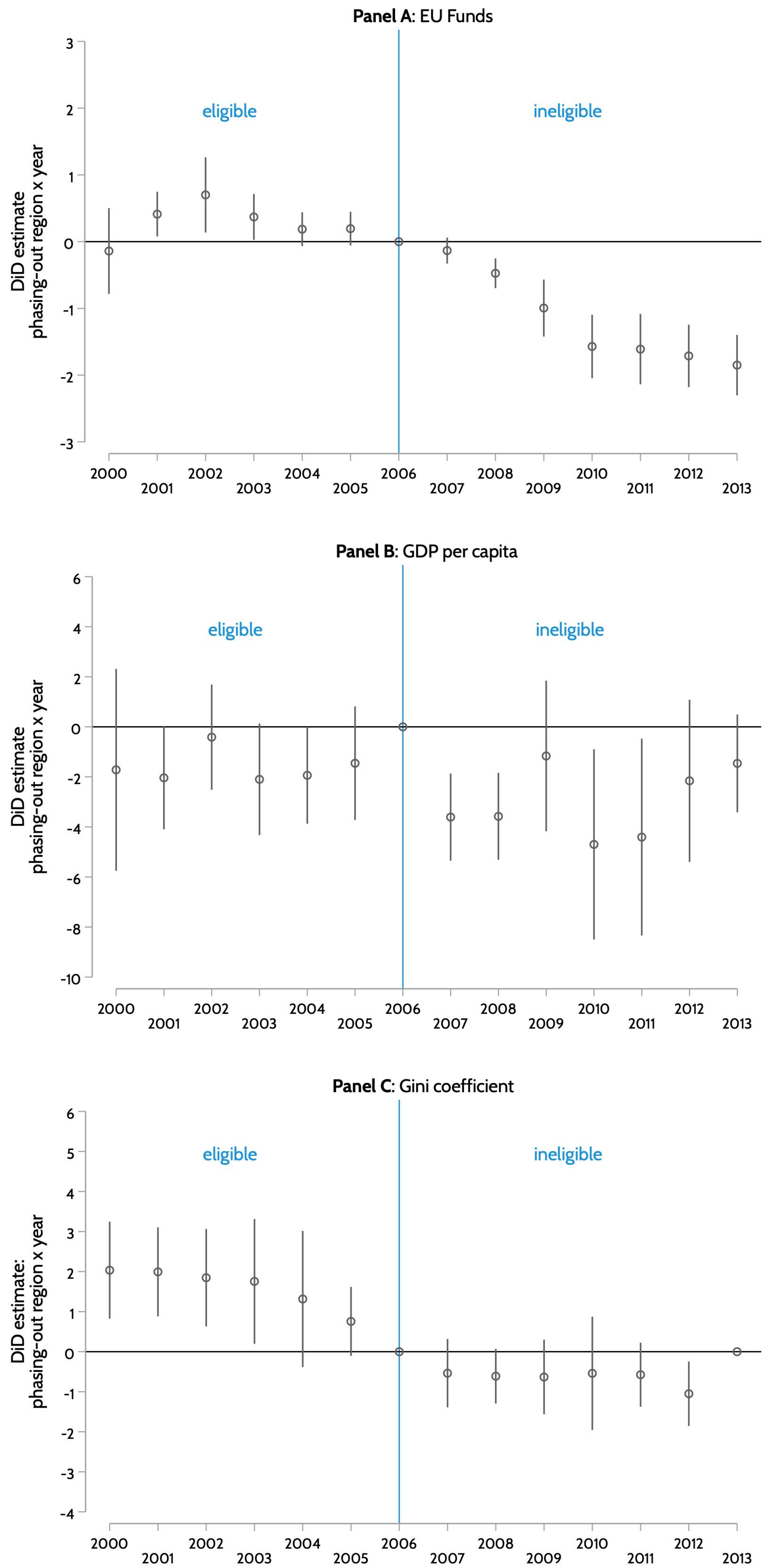
Panel B turns to annual growth rates of GDP per capita to see how average incomes reacted to this loss in place-based funding. There are no statistically significant differences between *phasing-out* regions and control regions before the former lose eligibility. The first significantly negative coefficient is observable in 2007, the first year after the dropout. The drop in the growth rate is thus immediately observable. For the subsequent 5 years, the annual growth rates are substantially lower in regions that lost much of their place-based funding. It also becomes visible that the trend in growth rates does not perfectly mirror the trend in funding volumes. Importantly, the drop in the growth rate is immediately visible in 2007, while the drop in disbursements is more lagged. This could suggest that the anticipated loss in place-based funding also affected investment decisions before actual disbursements stopped flowing into the regions. Final decisions on eligibility in the 2007-2013 funding period were already made in May 2006.[33]

Panel C turns to the Gini coefficient. It becomes visible that the relative drop in inequality levels occurs between 2005 and 2007. As for average incomes, this is likely to reflect changing investment decisions as soon as the loss of place-based funding could already be anticipated in May 2006. For the entire post-2006 period, estimated differences between *phasing-out* and control regions are substantially below all pre-2006 differences. This adds to the evidence that the place-based policy increased income inequality within regions. As soon as access to the funds was lost, inequality levels in supported regions declined.

Overall, the DiD results that leverage reductions in place-based funding are less precisely estimated and less clear-cut than the RD results. Arguably, this is due to the substantially smaller sample that can be used for this exercise. Nevertheless, these results are in line with and further support the main conclusions from the RD analysis: The place-based policy increases both average incomes and income inequality within regions.

[33]See: https://www.europeansources.info/record/in-focus-financial-perspectives-2007-2013-adopted-may-2006/

Figure 14: When Place-Based Funding Ends: Event Study



Notes: Regression result of the event-study model (see equation 7), estimated by OLS. The figures plot the estimates of β_t along with 95% confidence intervals. Outcome variables are EU Funds as a share of local GDP (Panel A), GDP per capita growth (Panel B) and the Gini coefficient [0,100] (Panel C). Estimates are relative to the year 2006, the last year of eligiblity.

7 Conclusions

Inequality across regions has been identified as a major challenge in most advanced economies. To fight inequalities and to foster economic convergence across regions, policymakers direct large sums of money to poor regions. But income inequality in such regions is large. As our new data show, inequality in Europe is to a large extent driven by inequality *within* regions. Hence, providing economic support to so-called *left-behind regions* does not necessarily mean that this reaches the most *left-behind people*. So far, it was unclear whether place-based policies generate income gains for the rich or the poor in the regions that they target.

We find that one of the world's largest place-based policies benefits rich people in supported regions much more than it benefits the region's poor. As a consequence, these funds help reduce inequality *across* regions but they exacerbate inequality *within* regions. While we find strong positive effects on average economic growth, the policy does not lift the incomes of the poor in these regions. This result is driven by increases in labor income for the richest income deciles and the most highly educated. These income groups seem to be in better positions to reap the policy's benefits.

While our study identifies this pattern for one of the most prominent place-based policies, it would be important to test whether effects are similar in other contexts. More generally, the literature on regional policies could benefit from shifting the focus from average growth effects to distributional effects.

For policymaking, our results do not imply that place-based policies are ineffective. If the goal is to reduce inequality across regions, they are powerful tools in the hands of policymakers. However, their potential to address overall inequality and providing relief to the poor seems severely limited – at least unless they are coupled with rules that ensure a more egalitarian distribution of place-based support. How such policies could be designed is an important question for subsequent research.

Another promising avenue for future research relates to the *political* effects of place-based policies. Policymakers often portray these policies as tools to counter political frustration in left-behind regions. But if they fail to reach the most left-behind people in the regions that they target, it is doubtful whether they actually deliver on this promise. Quite the opposite, their distributional effects might even exacerbate political discontent and reinforces feelings of left-behind. In the context of growing political polarization across regions, research on this question seems timely.

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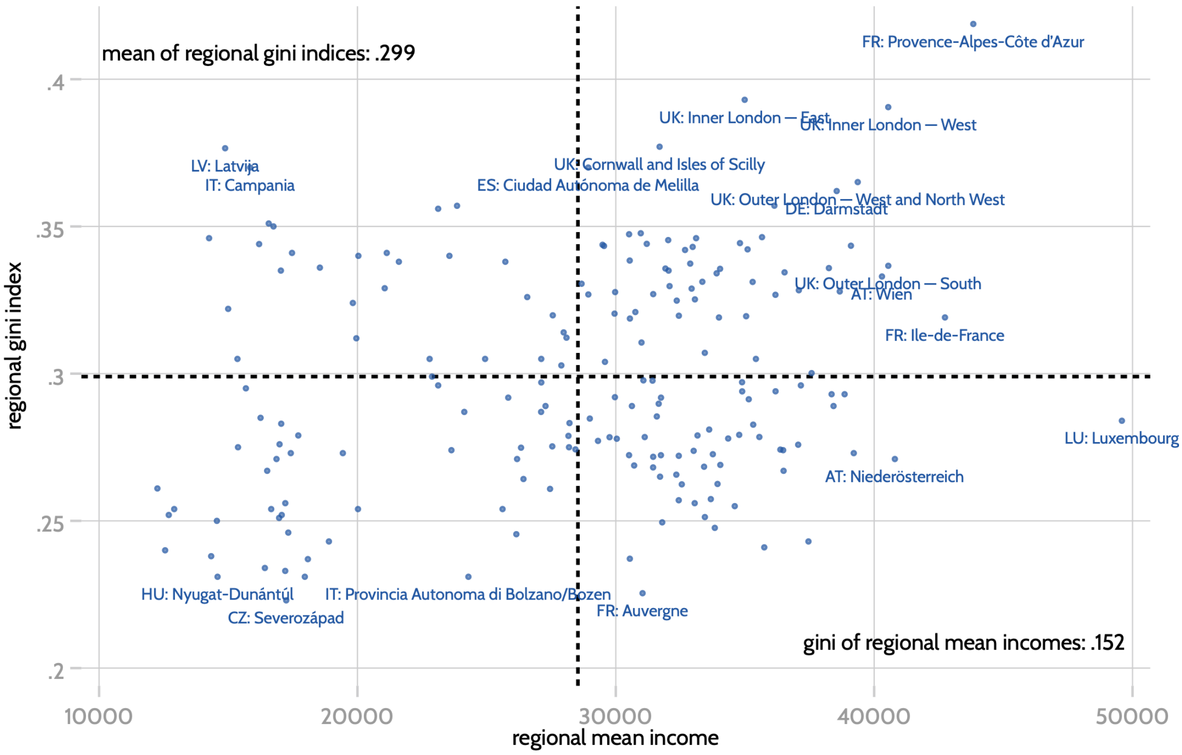
SI Supporting Information

Contents

SI.1 Data on European Inequality and Validation of Data Quality

In Figure SI 1, we plot regional gini indices against the regional mean of disposable household incomes. As before, we see substantial variation in both regional mean incomes and intra-regional inequality across European regions. The cross-regional Gini coefficient of regional mean incomes is at 0.18 and thus considerably smaller than the average intra-regional Gini coefficient of 0.3. Overall, there seems to be a weak positive association between regional mean incomes and inequality. While richer regions tend to be more unequal, on average, there are both relatively unequal and relatively equal among the poorer regions. t there is no strong relationship between mean incomes and income inequality across European regions. On average, richer regions are somewhat more unequal.

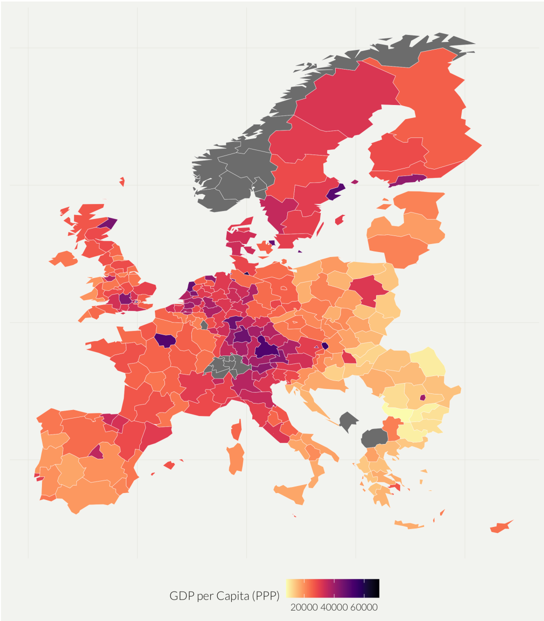
Figure SI 1: Regional gini indices and regional mean income



Notes: The figure plots regional mean incomes on the x-axis against regional gini indcies on the y-axis, latest available year.

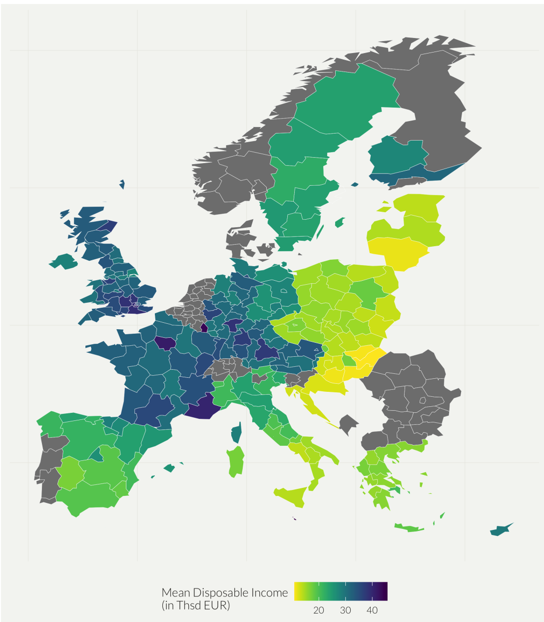
The two maps show regional levels of GDP per capita from national accounts (Figure SI 2) and the regional mean of disposable household income from the national surveys (Figure SI 3). The strong correlation is visible.

Figure SI 2: Regional GDP per capita (national accounts)



Notes: The map plots regional GDP per capita, latest available year.

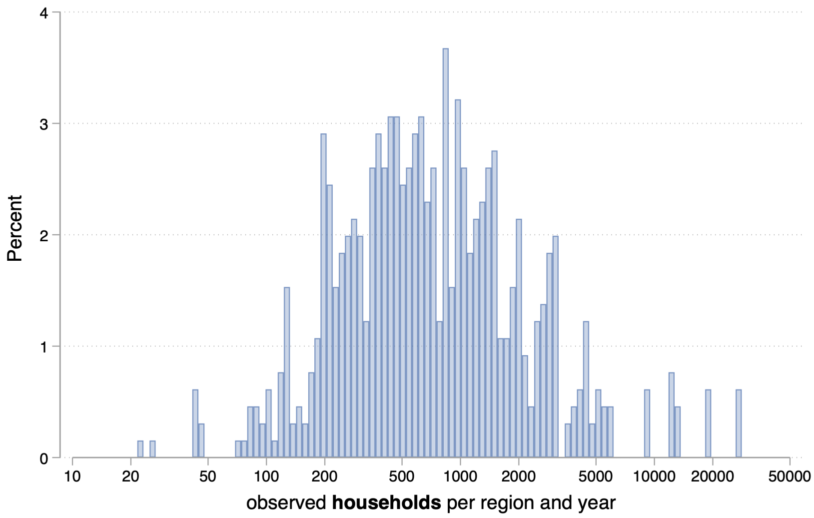
Figure SI 3: Regional mean disposable household income (household surveys)



Notes: The map plots regional means of disposable household income, latest available year.

To address the potential concern that the number of survey respondents per region-year might be too small, Figure SI 4 shows a histogram of the available number of survey respondents per region and year. For most regions and years, these surveys contain income data from a sufficiently large number of households. In the mean (median) region-year we observe 1644 (852) individuals. In order to mitigate small-sample problems, we exclude all region-years for which we cover fewer than 500 survey respondents in the baseline analysis. And in robustness tests, we show that the results are robust to dropping this restriction.

Figure SI 4: Number of survey respondents per NUTS2-region and year



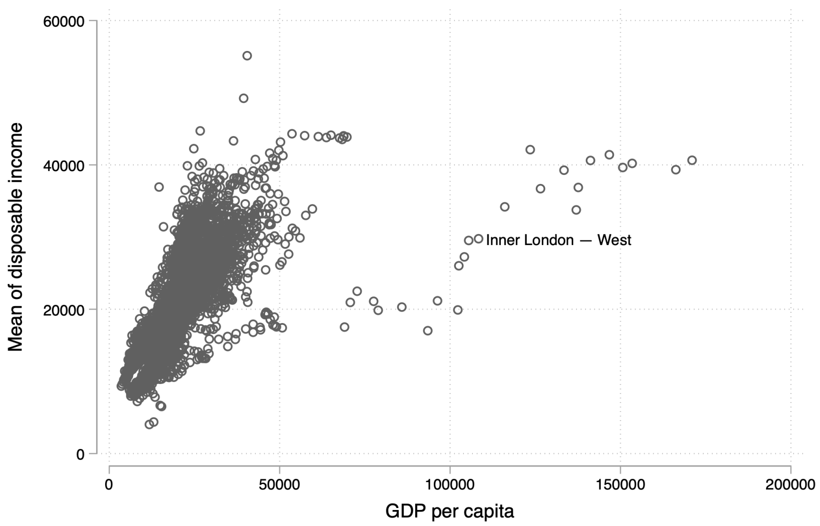
Notes: Histogram. x-axis in log scale.

To further validate the quality of our income survey data, we examine correlations between the region-year-specific mean income that we calculate from these data and the region-year-specific GDP measures that originate from national accounts. Although these two measures are not identical concepts they should be highly correlated if measurement error is small.

Figure SI 5 shows a scatter plot of these two measures. As is visible, correlations are consistently positive and strong. The overall correlation coefficient of the two measures is 0.77. Figure SI 6 shows country-wise scatter plots. The country-wise correlations coefficients range between 0.62 and 0.99.

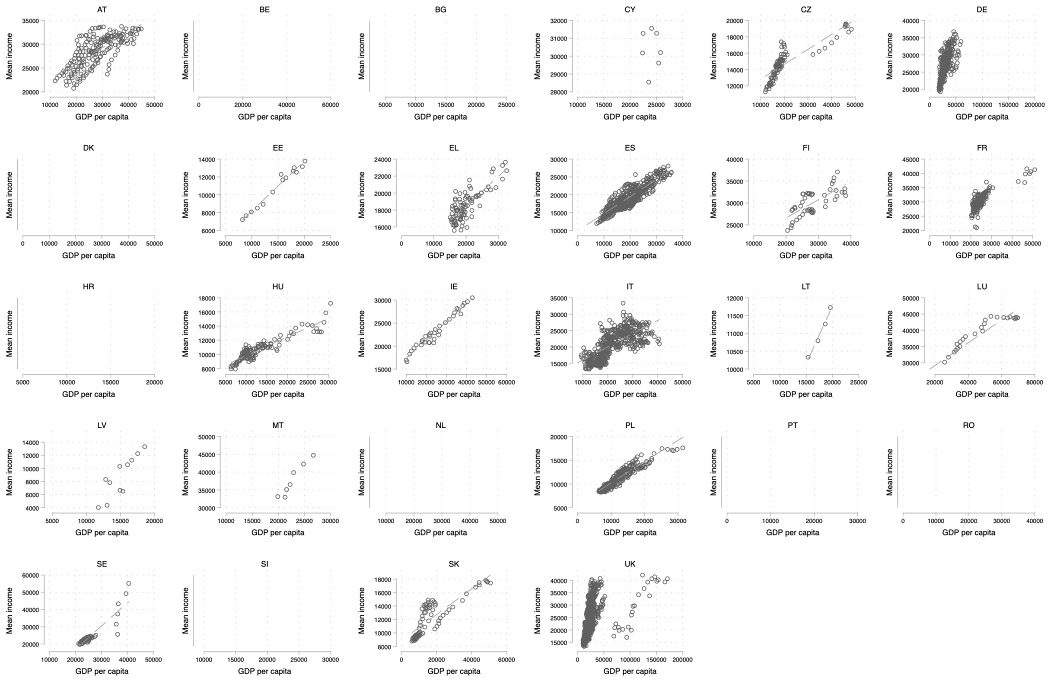
A notable and instructive outlier is London. All values in the figure with a GDP per capita above 70.000 are observations from the NUTS2-region UKI3 "Inner London - West." A large share of the United Kingdom's GDP is produced here. Disposable incomes in London, however, do not reach the same level as other regions with similarly high levels of GDP per capita. One explanation for this result is commuting: London is the European region "with the highest number of commuters" (Eurostat 2018). And as the European Commission states: "there are a number of regions where people work but do not live, commuting between the region where they live and the region where they work. For these regions, the concept of GDP per head does not make sense as a measure of the level of development" (Monfort 2020).

Figure SI 5: Regional mean income and regional GDP per capita



Notes: The figure plots GDP per capita on the x-axis against the regional mean of disposable household income. The outlying observations on the right are all from *Inner London, West*

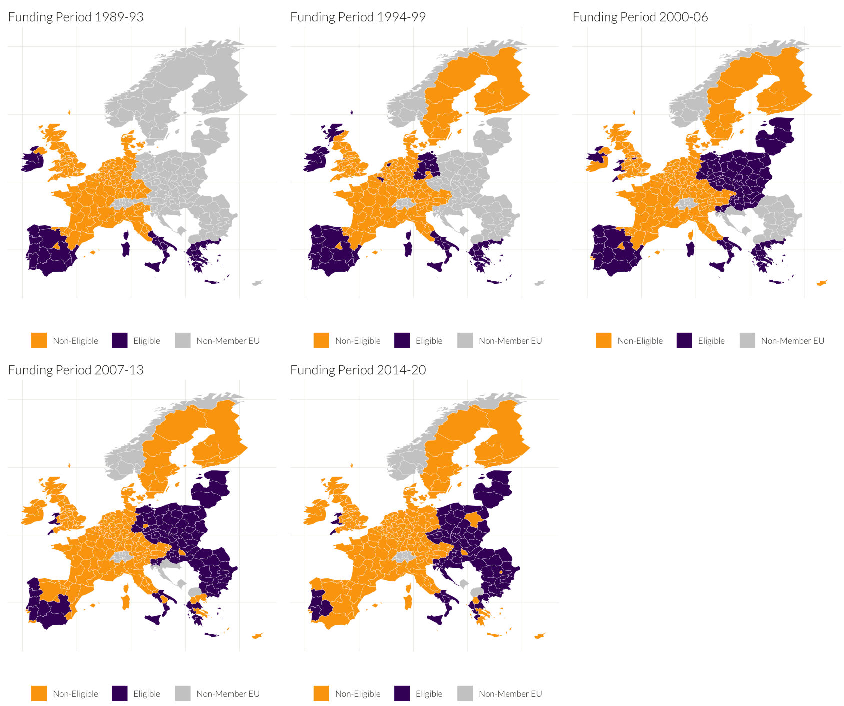
Figure SI 6: Regional mean income and regional GDP: correlations by country



Notes: The figure plots regional GDP per capita on the x-axis against the regional mean of disposable household income for each country in the sample.

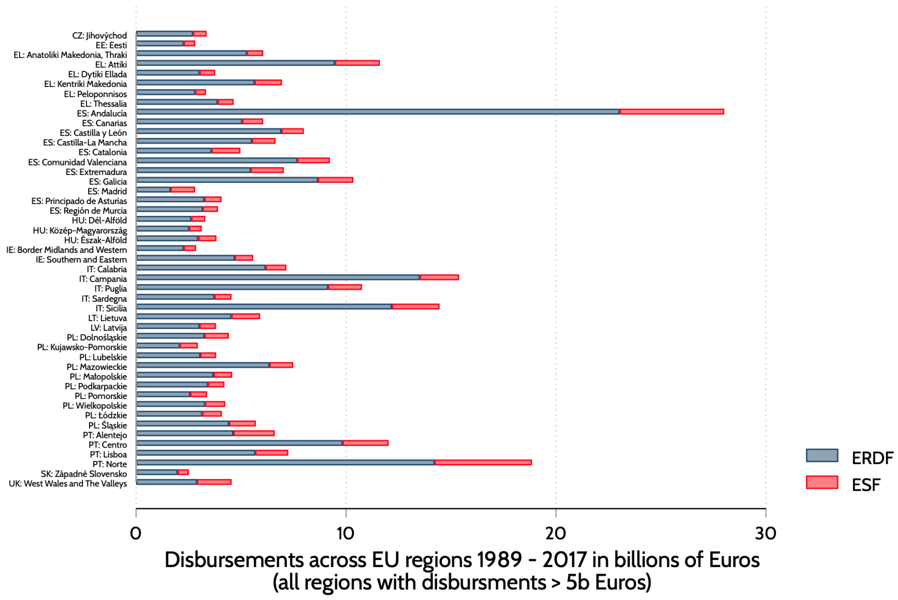
SI.2 Data on Treatment Variables

Figure SI 7: Eligibility over time



Notes: The map indicates the regions that were officially *eligible* to receive the bulk of EU funds.

Figure SI 8: Data on EU Structural Funds: Disbursements of EU Funds across regions



SI.3 Exceptions to the 75%-rule

Table SI 1: Exceptions to the 75%-rule

Region	NUTS2 code	Funding Period	GDP per capita (% EU average)	Explanation for Exception
Hainaut	BE32	1994-1999	77.28	GDP per capita "close to" threshold and "special reason": high unemployment and declining industries.
Hainaut	BE32	2000-2006	81.30	Exceptional transitional support
Sterea Ellada	EL64	1989-1993	80.42	GDP per capita "close to" threshold and "special reason": In this funding period, all Greek regions were eligible because of Greece's low GDP per capita
Sterea Ellada	EL64	1994-1999	75.97	GDP per capita "close to" threshold and "special reason": In this funding period, all Greek regions were eligible because of Greece's low GDP per capita
Asturias	ES12	1989-1993	76.64	GDP per capita "close to" threshold
Cantabria	ES13	1994-1999	75.52	GDP per capita "close to" threshold
Corse	FR83	1989-1993	84.73	"Special reasons": remoteness
Corse	FR83	1994-1999	83.26	"Special reasons": remoteness
Abruzzo	ITF1	1989-1993	89.14	"Special reasons": high unemployment
Abruzzo	ITF1	1994-1999	89.49	"Special reasons": high unemployment. Exception coninued only until 1996 because GDP per capita exceeded the threshold
Molise	ITF2	1989-1993	76.17	GDP per capita "close to" threshold and "special reason": high unemployment.
Molise	ITF2	1994-1999	78.32	GDP per capita "close to" threshold and "special reason": high unemployment.
Sardegna	ITG2	1989-1993	75.63	GDP per capita "close to" threshold and "special reason": high unemployment.
Flevoland	NL23	1994-1999	76.88	GDP per capita "close to" threshold and below threshold in the late 1980s
Northern Ireland	UKN0	1994-1999	75.84	GDP per capita "close to" threshold and "special reason": The Troubles.

Note: This table lists all regions that received eligibility status even though their GDP per capita exceeded the threshold value. See Figure 7.
Sources: https://ec.europa.eu/regional_policy/sources/docgener/evaluation/doc/obj1/belgium.pdf;
https://ec.europa.eu/regional_policy/en/atlas/programmes/2000-2006/belgium/objective-1-programme-of-transitional-support-for-hainaut;
https://ec.europa.eu/regional_policy/sources/docgener/evaluation/doc/obj1/greece.pdf;
https://ec.europa.eu/regional_policy/sources/docgener/evaluation/doc/obj1/spain.pdf;
https://ec.europa.eu/regional_policy/sources/docgener/evaluation/doc/obj1/france.pdf;
https://www.bancaditalia.it/pubblicazioni/temi-discussione/2016/2016-1071/en_tema_1071.pdf;
https://ec.europa.eu/regional_policy/sources/docgener/evaluation/doc/obj1/netherlands.pdf;
https://ec.europa.eu/regional_policy/sources/docgener/evaluation/doc/obj1/uk.pdf

SI.4 Additional Results on Mechanisms

SI.4.1 Unemployment

Table SI 2: Unemployment

	DV: Change in unemployment rate		
	overall unemployment	long-term unemployment	youth unemployment
Eligibility	-0.42	-0.49	-1.00
	(0.09)	(0.05)	(0.12)
Country FE and Year FE	✓	✓	✓
Mean of Outcome	8.6	4.2	21.1
Observations	905/1916	802/1448	973/1823

Notes: The table reports local linear RD estimates with robust nonparametric standard errors clustered at the NUTS2-level and reported in parentheses. The forcing variable is regional GDP per capita as a share of the EU average. The cutoff is at 75%. The bandwidth is 40. All estimations use a triangular kernel.

SI.4.2 Rural and Urban Places within Regions

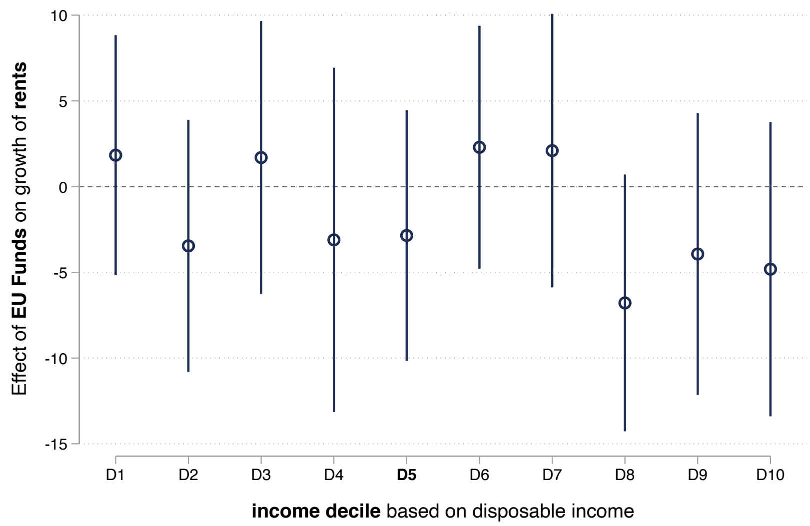
Table SI 3: Rural and Urban Places

	DV: Income growth	
	Rural	Urban
Eligibility	1.443	0.732
	(0.631)	(0.411)
Country FE and Year FE	✓	✓
Observations	401/443	405/474
Mean income	19457	21232

Notes: The dependent variables are growth of disposable household income by level of education per region and year. The table reports local linear RD estimates with robust nonparametric standard errors clustered at the NUTS2-level and reported in parentheses. The forcing variable is regional GDP per capita as a share of the EU average. The cutoff is at 75%. The bandwidth is 40. All estimations use a triangular kernel.

SI.4.3 Rents

Figure SI 9: Effect on housing costs by decile



Notes: Coefficients of **EU Funds** and 95% confidence intervals. The dependent variable is the growth of housing costs for the ten deciles by disposable income. Otherwise the regressions are identical to the baseline regressions plotted in figure 10.

SI.5 Robustness: RD

SI.5.1 Varying the Bandwidth

Figure SI 10: Varying the Bandwidth: Effects on **EU Funds**

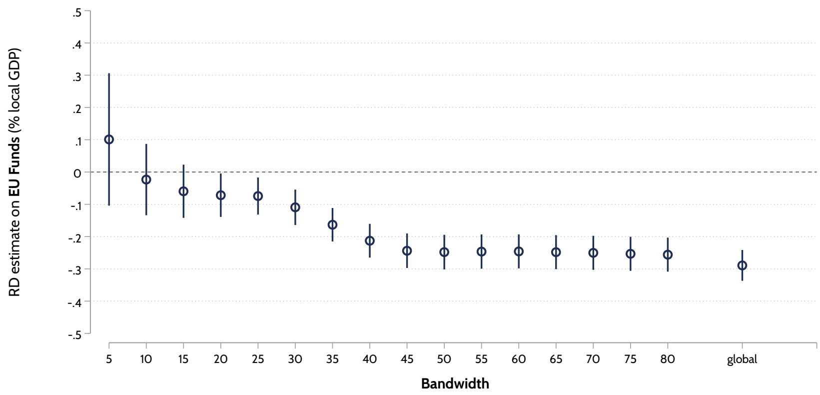


Figure SI 11: Varying the Bandwidth: Effects on **GDP Growth**

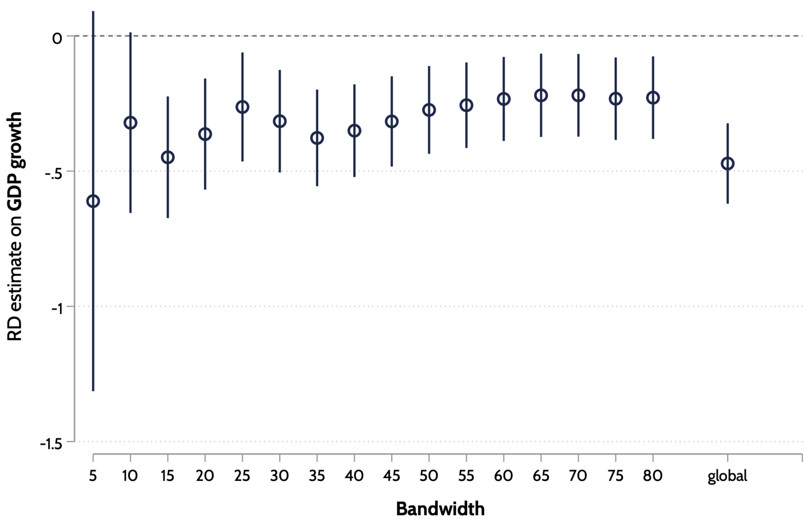


Figure SI 12: Varying the Bandwidth: Effects on **Growth of Household Incomes**

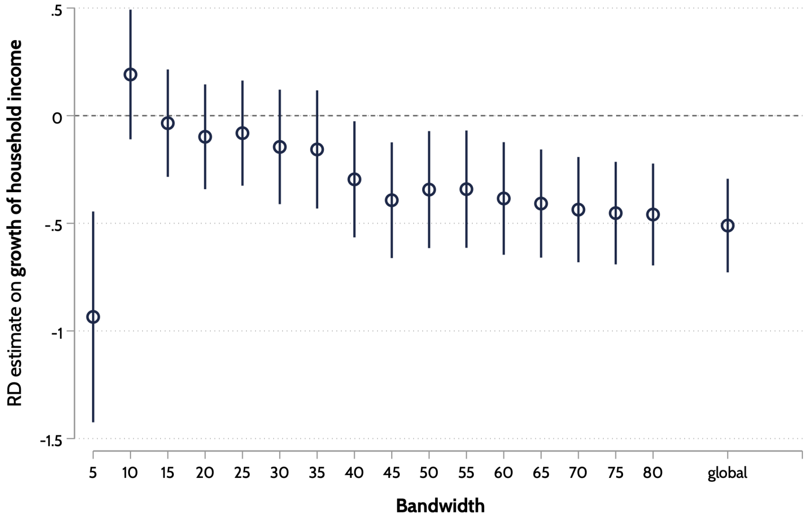
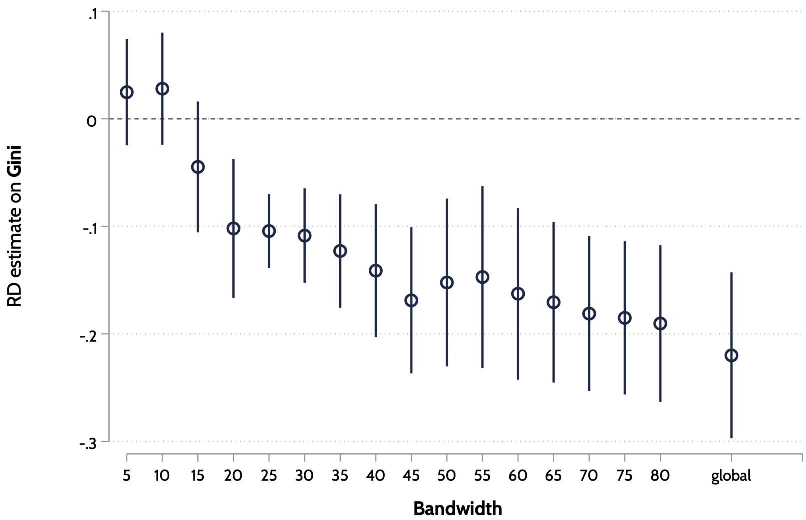


Figure SI 13: Varying the Bandwidth: Effects on **Inequality of Household Incomes**



SI.5.2 Uniform Kernels

Figure SI 14: Uniform Kernel: Effects on **EU Funds**

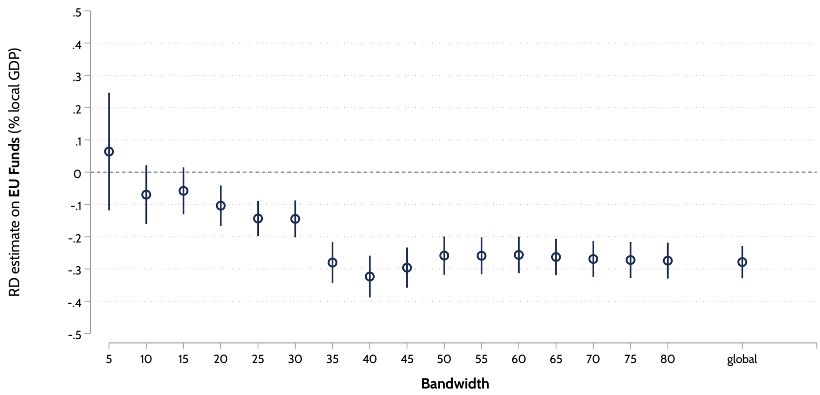


Figure SI 15: Uniform Kernel: Effects on **GDP Growth**

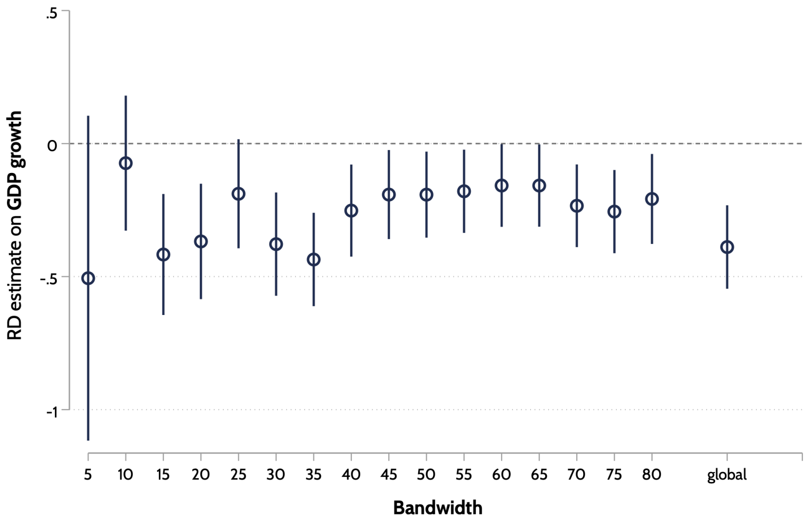


Figure SI 16: Uniform Kernel: Effects on **Growth of Household Incomes**

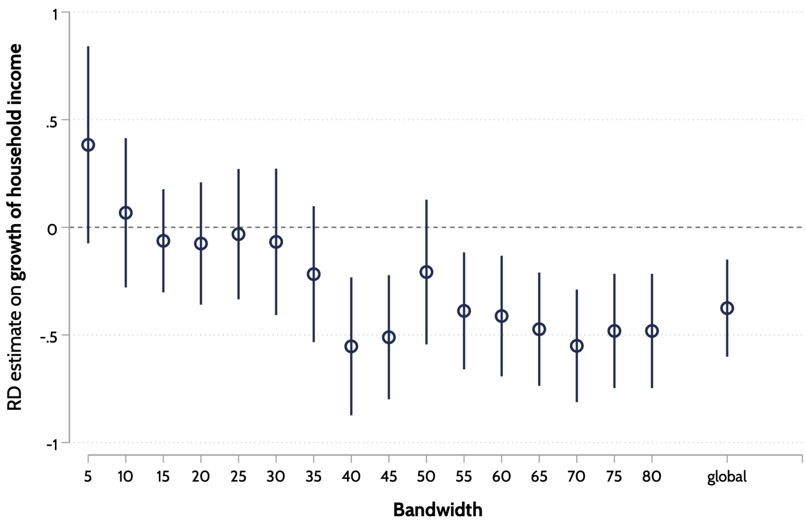
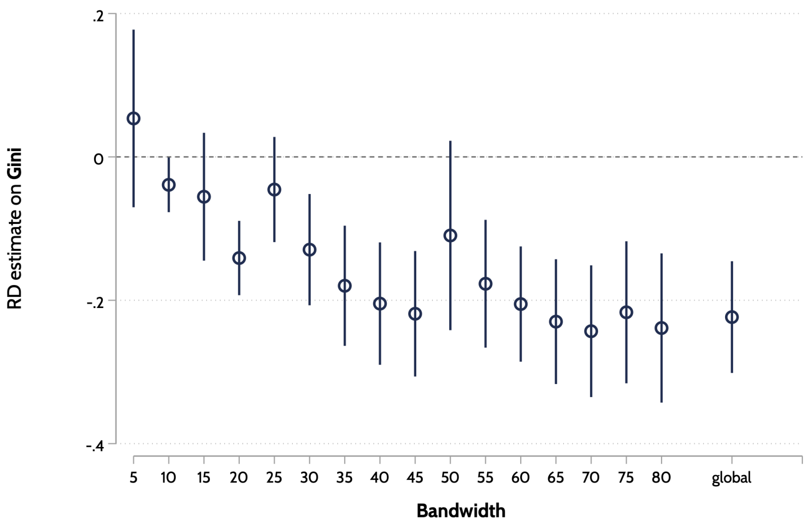


Figure SI 17: Uniform Kernel: Effects on **Inequality of Household Incomes**



SI.5.3 Excluding Exceptions

Table SI 4: Excluding Exceptions

Intention-to-Treat Effect *(Sharp RD)*	(1) GDP per capita	(2) Household income	(3) Gini
Above cutoff (75%)	-0.71 (0.10)	-0.48 (0.14)	-0.18 (0.04)
Country FE and Year FE	✓	✓	✓
Observations	1262/3089	549/614	575/646
Local Average Treatment Effect *(Fuzzy RD)*	(1) GDP per capita	(2) Household income	(3) Gini
Eligibility	0.70 (0.10)	0.48 (0.14)	0.18 (0.04)
Country FE and Year FE	✓	✓	✓
Observations	1261/3053	549/614	575/646

Notes: The sample excludes regions that are officially *eligible* even though they are above the cutoff. The table reports local linear RD estimates with robust nonparametric standard errors clustered at the NUTS2-level and reported in parentheses. The forcing variable is regional GDP per capita as a share of the EU average. The cutoff is at 75%. The bandwidth is 40. All estimations use a triangular kernel.

SI.5.4 Donut RD

Table SI 5: Donut RD

Intention-to-Treat Effect *(Sharp RD)*	(1)	(2)	(3)	(4)
Above cutoff (75%)	-0.35	-0.23	-0.35	-0.44
	(0.09)	(0.10)	(0.14)	(0.12)
Country FE and Year FE	✓	✓	✓	✓
Observations	1267/3171	1174/3119	1103/3068	1056/3024
Size of Donut Hole	+/- 0	+/- 1	+/- 2	+/- 3
Local Average Treatment Effect *(Fuzzy RD)*	(1)	(2)	(3)	(4)
Eligibility	0.49	0.29	0.39	0.50
	(0.11)	(0.11)	(0.16)	(0.13)
Country FE and Year FE	✓	✓	✓	✓
Observations	1266/3135	1173/3083	1102/3032	1055/2988
Size of Donut Hole	+/- 0	+/- 1	+/- 2	+/- 3

Notes: The sample excludes observations close to the cutoff. Local Linear RD Estimation. The table reports local linear RD estimates with robust nonparametric standard errors clustered at the NUTS2-level and reported in parentheses. The forcing variable is regional GDP per capita as a share of the EU average. The cutoff is at 75%. The bandwidth is 40. All estimations use a triangular kernel.

SI.5.5 Including Regions with Fewer Survey Respondents

Table SI 6: Including Regions with Fewer Survey Respondents

Intention-to-Treat Effect *(Sharp RD)*				
	Mean	Mean	Gini	Gini
Above cutoff (75%)	-0.30	-0.28	-0.14	-0.13
	(0.14)	(0.14)	(0.03)	(0.03)
Country FE and Year FE	✓	✓	✓	✓
Observations	549/623	808/1664	575/657	841/1739
Sample restricted	✓	-	✓	-

Local Average Treatment Effect *(Fuzzy RD)*				
	Mean	Mean	Gini	Gini
Eligibility	0.40	0.33	0.18	0.16
	(0.15)	(0.15)	(0.04)	(0.03)
Country FE and Year FE	✓	✓	✓	✓
Observations	549/623	808/1664	575/657	841/1739
Sample restricted	✓	-	✓	-

Notes: If the sample is not restricted, it *includes* regions with less than 500 survey respondents. The table reports local linear RD estimates with robust nonparametric standard errors clustered at the NUTS2-level and reported in parentheses. The forcing variable is regional GDP per capita as a share of the EU average. The cutoff is at 75%. The bandwidth is 40. All estimations use a triangular kernel.

SI.6 Robustness: Surveys among Recipients

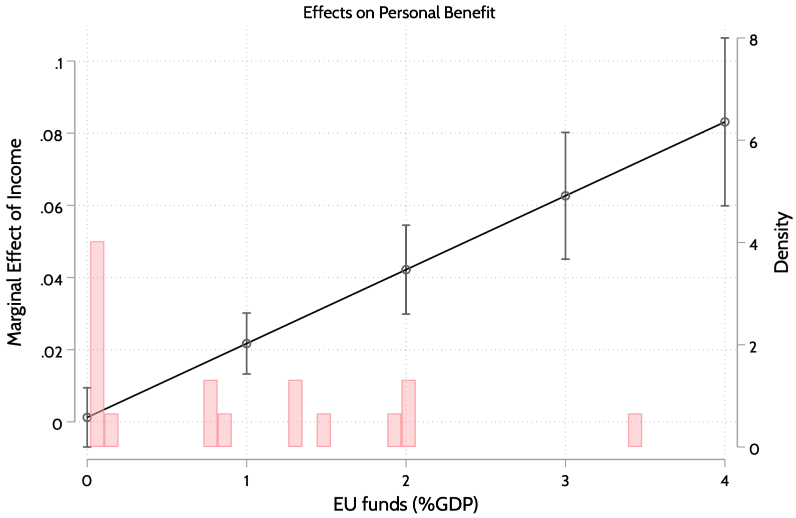
Table SI 7: Self-reported Personal Benefit: Survey Evidence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Income	0.014	0.013	-0.002				0.008
	(0.005)	(0.005)	(0.003)				(0.005)
Income × EU funds (% GDP)			0.016				
			(0.003)				
Education				0.028	0.027	0.019	0.026
				(0.004)	(0.003)	(0.003)	(0.003)
Education × EU funds (% GDP)						0.008	
						(0.003)	
EU funds (% GDP)	0.004			0.005			
	(0.016)			(0.014)			
Age	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Agricultural Sector	0.020	0.031	0.032	0.041	0.049	0.052	0.050
	(0.025)	(0.022)	(0.022)	(0.026)	(0.023)	(0.023)	(0.023)
Heard of ERDF	0.150	0.127	0.127	0.132	0.115	0.114	0.114
	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Heard of ESF	0.100	0.101	0.100	0.098	0.097	0.097	0.097
	(0.015)	(0.013)	(0.013)	(0.014)	(0.012)	(0.012)	(0.012)
Region FE		✓	✓		✓	✓	✓
Regions	17	17	17	17	17	17	17
Observations	8451	8451	8451	8451	8451	8451	8451

Notes: OLS regressions standard errors, robust to clustering at the region level, in parentheses. Outcome variable: Binary indicator for respondents who state that they "personally benefited" from a project funded by EU Funds.

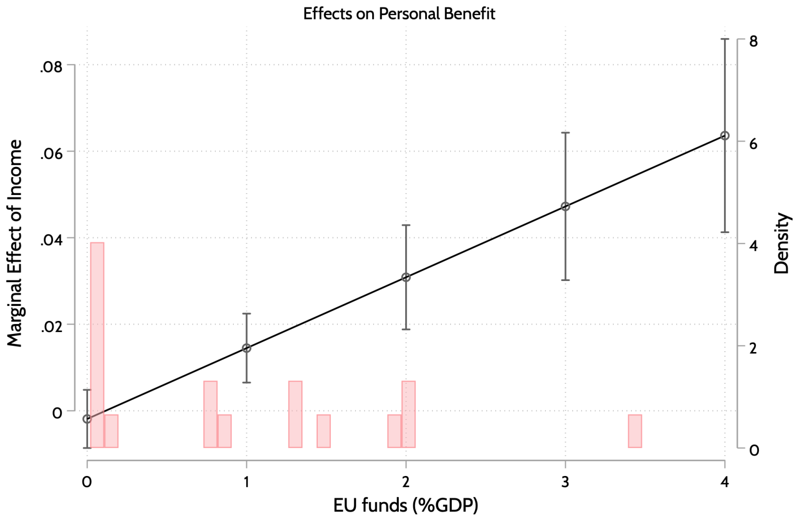
SI.6.1 Surveys among Recipients: Marginal-Effect Plots

Figure SI 18: Survey: Marginal Effects of Interaction



Notes: The figure plots marginal effects of *income* on *self-reported personal benefit from EU funds* for different levels of *EU funds (%GDP)* based on results reported in Table 7. 95% confidence intervals.

Figure SI 19: Survey: Marginal Effects of Interaction

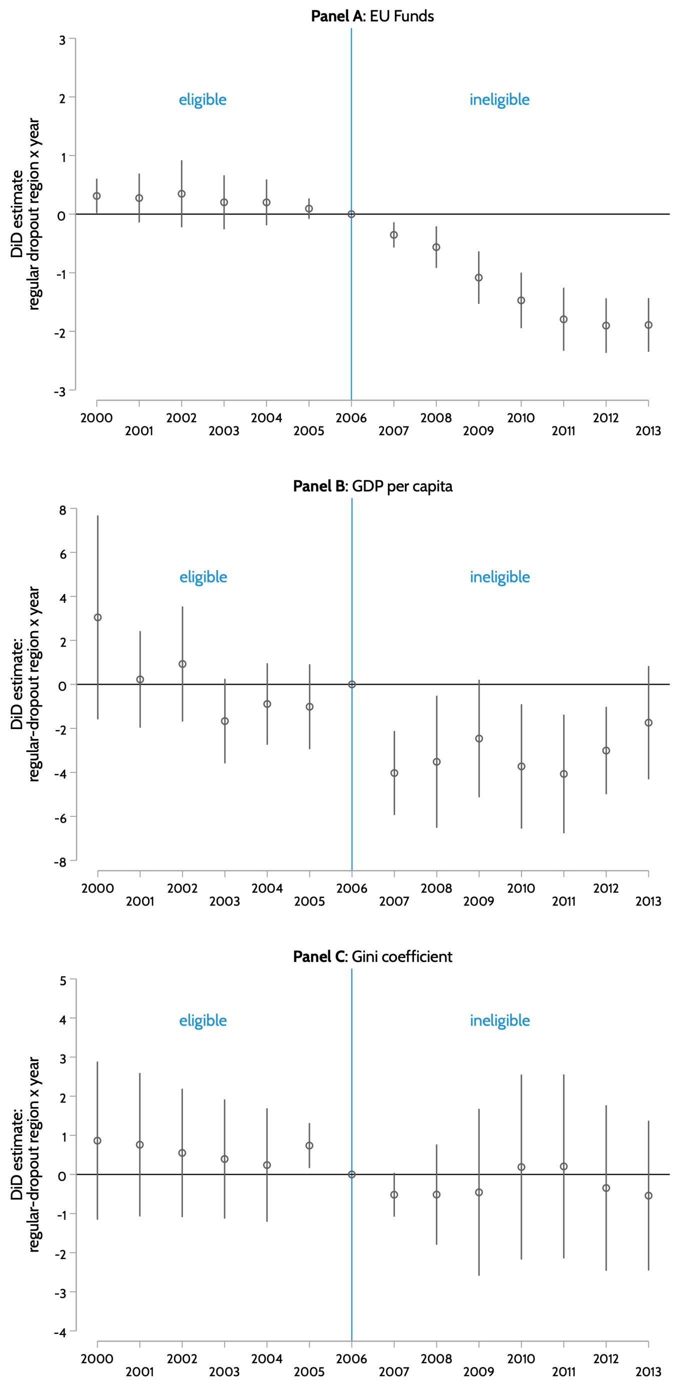


Notes: The figure plots marginal effects of *income* on *self-reported personal benefit from EU funds* for different levels of *EU funds (%GDP* based on results reported in Table SI 7. 95% confidence intervals.

SI.7 Robustness: DiD

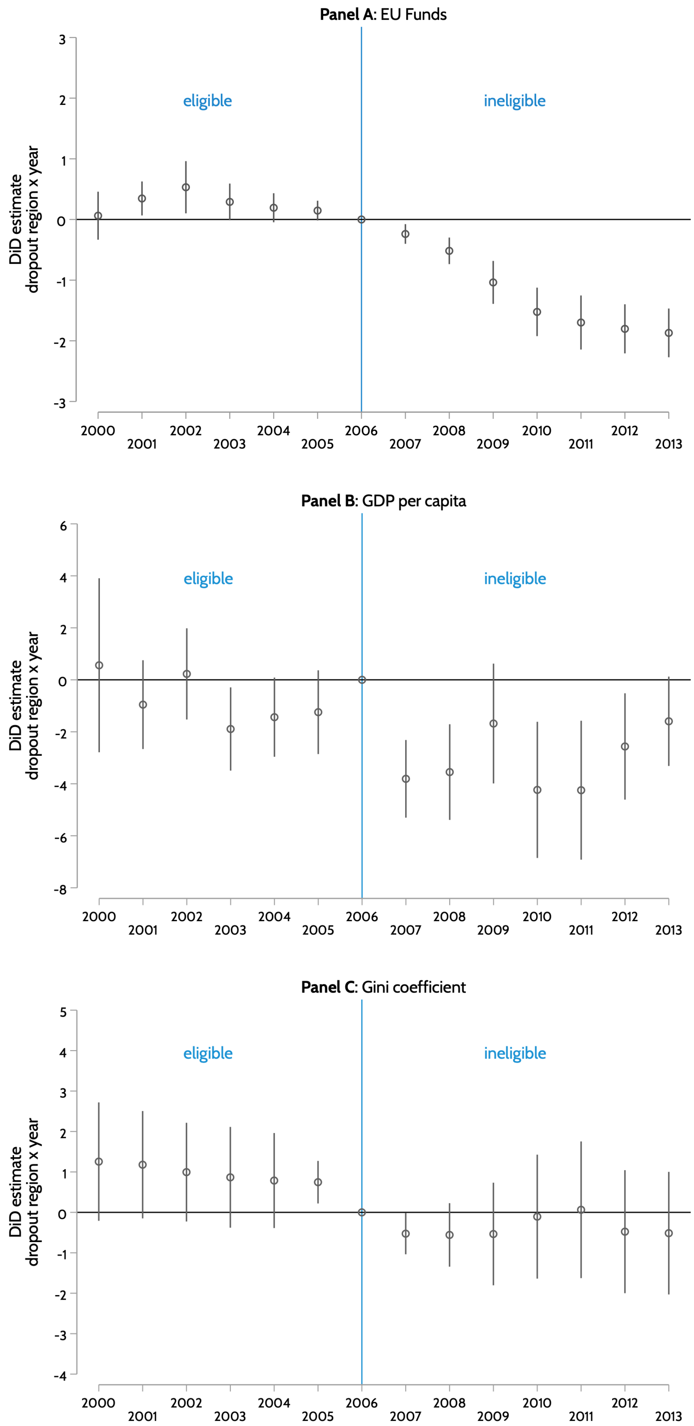
SI.7.1 DiD: Additional Results

Figure SI 20: Event Study: Only Regular Drop-Out Regions



Notes: Regression result of the event-study model (equation 7), estimated by OLS. The figures plot the estimates of β_t along with 95% confidence intervals. Outcome variables are EU Funds as a share of local GDP (Panel A), GDP per capita growth (Panel B) and the Gini coefficient [0,100] (Panel C). Estimates are relative to the year 2006, the last year of eligibility. In contrast to the main model, this model considers *regular* drop-out regions as treated units.

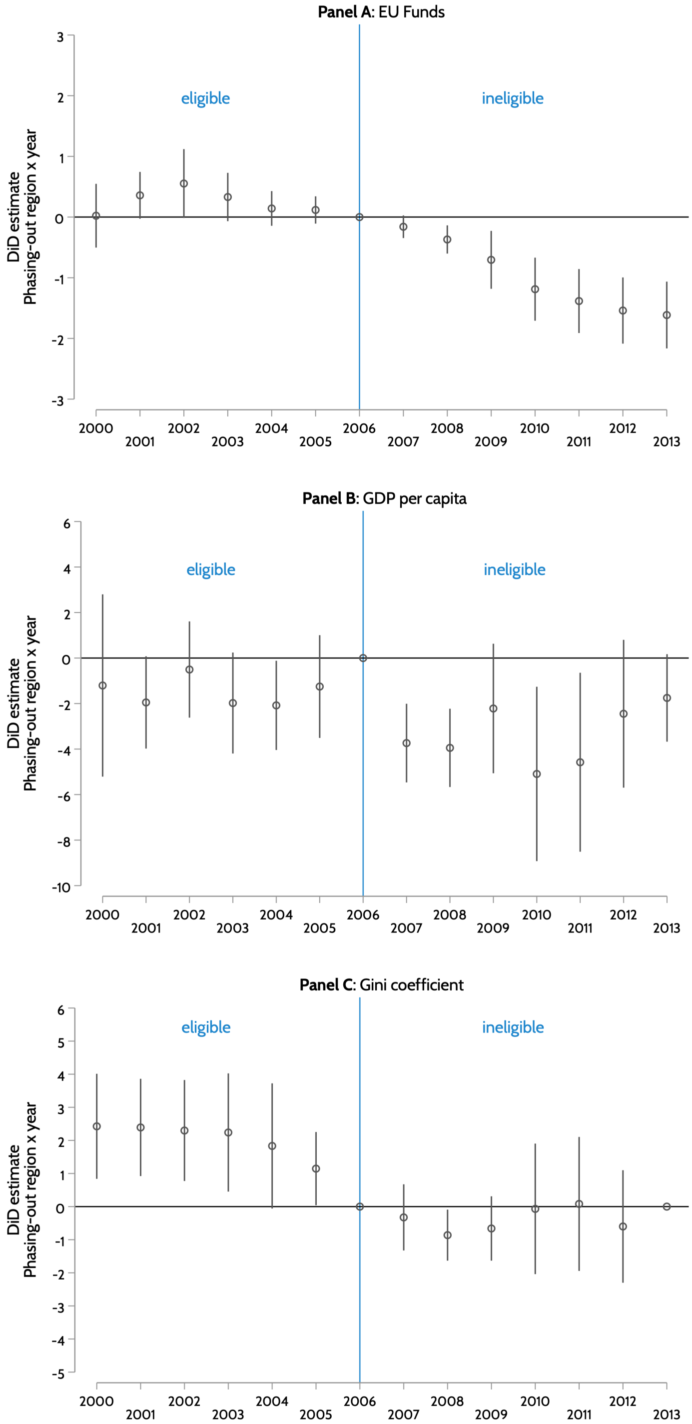
Figure SI 21: Event Study: All Drop-Out Regions



Notes: Regression result of the event-study model (equation 7), estimated by OLS. The figures plot the estimates of β_t along with 95% confidence intervals. Outcome variables are EU Funds as a share of local GDP (Panel A), GDP per capita growth (Panel B) and the Gini coefficient [0,100] (Panel C). Estimates are relative to the year 2006, the last year of eligibility. In contrast to the main model, this model considers *all* drop-out regions as treated units.

SI.7.2 DiD matching

Figure SI 22: Event Study with Propensity Score Matching



Notes: Regression result of the event-study design with propensity-score matching. The figures plot the estimates of β_t of equation 7. Outcome variables are EU Funds as a share of local GDP (Panel A), GDP per capita growth (Panel B) and the Gini coefficient [0,100] (Panel C). Estimates are relative to the year 2006, the last year before the loss of eligiblity. Plotted are point estimates along with 95% confidence intervals.