PLACE-BASED INDUSTRIAL POLICIES AND INEQUALITY WITHIN REGIONS [*]

Valentin Lang[◇]
Nils Redeker[§]
Daniel Bischof[‡]

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Abstract

What are the distributional effects of placed-based policies? Drawing on household data from 2.4 million survey respondents in the European Union (EU), we show that income inequality within European regions is substantial, has widened since the 1990s and contributes more to overall inequality than cross-regional inequality. Using regression discontinuity and difference-in-differences designs, we find that the world's largest place-based policy, the EU's Cohesion Policy, increases disposable income for affluent households but barely affects low-income households in supported regions. Evidence on mechanisms demonstrates that place-based funds exacerbate intra-regional inequality by primarily boosting labor income for the highly skilled.

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[◇]lang@uni-mannheim.de; University of Mannheim, A5, 6, 68131 Mannheim, Germany; +49 621 181 3641; corresponding author.

[§]redeker@delorscentre.eu; Hertie School Berlin, Jacques Delors Centre; Alexanderstr. 3, 10178 Berlin, Germany; + 49 30 259 219 219.

[‡]dan.bischof@uni-muenster.de; University of Muenster; ScharnhorststraÃe 100, 48151 MuÌnster, Germany & bischof@ps.au.dk; Aarhus University; Bartholins Alle 7, 8000 Aarhus C, Denmark; +45 87 16 56 15.

1 Introduction

Placed-based economic policies have become ubiquitous. As globalization, technological change, and agglomeration economies increasingly concentrate economic activity in certain places (Autor et al. 2013; Gaubert et al. 2021b; Dauth et al. 2022), policymakers are putting more and more resources into countering the rise of economic hardship and political frustration in places that are left behind (Colantone and Stanig 2018a,b,c; Autor et al. 2020; Bisbee et al. 2020). The US government spends about USD 60 billion per year on various regional economic policies (Bartik 2020) and the European Union (EU) recently increased its annual budget for regional development to more than EUR 50 billion. Moreover, current industrial policy pushes, such as the Infrastructure Investment and Jobs Act or the Inflation Reduction Act in the US, also have clear place-based elements (Muro et al. 2022). A growing literature finds that such place-based policies can promote regional economic growth, productivity and employment (Becker et al. 2010; Busso et al. 2013; Seidel and von Ehrlich 2018; Criscuolo et al. 2019). So far, this research has mainly studied average effects (for reviews, see: Ehrlich and Overman 2020; Kline and Moretti 2014b; Moretti 2022). However, we lack evidence on how the benefits from place-based funding are distributed within supported regions (Neumark and Simpson 2015; Bartik 2020).[1]

How the gains of place-based policies are distributed within receiving regions matters for both efficacy and equity reasons. On efficacy, policymakers often promote regional policies as a means to support people in distressed communities. This builds on recent research that has made the case for place-based policies as tools to counter the negative effects that living in disadvantaged areas has on individual economic outcomes (Chetty and Hendren 2018; Chyn and Katz 2021), as instruments to create employment for poor and immobile workers (Bartik 2020), and as a way of reducing political discontent (Broz et al. 2021). The degree to which place-based policies can achieve these goals largely depends on whether they lift incomes and job opportunities for distressed people in distressed places. On equity, place-based policies are re-distributive. To support poorer regions they divert resources from more affluent places. However, as we show, income differences within regions are large. Just as not everyone in prosperous regions is rich, so not all people in left-behind regions are poor. To know whether placed-based policies genuinely support left-behind people in left-behind places or simply funnel resources to the rich living there we need to understand how gains from these policies are distributed within regions.

In this paper, we study the distributional effects of the world's largest place-based

[1] Neumark and Simpson (2015: p. 76) conclude their extensive literature review with the statement that "the evidence that place-based policies achieve their distributional goals is itself far from clear." In his review, Bartik (2020: p. 106) also discusses the lack of evidence on the question whether "the benefits of place-based jobs policies may be diverted to upper-income groups."

policy in the context of Europe. We proceed in three stages. We begin by constructing the first comprehensive panel 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 yearly panel of intra-regional income distributions across 231 European regions in the 1989-2017 period. These data allow us to derive stylized facts on the development of income inequality in Europe across and within regions.

As a second step, we use this 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 collected information on the EU's Cohesion Policy to examine how these place-based 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 employ a (fuzzy) regression discontinuity design (RDD) around the funding threshold to compare barely eligible with barely ineligible regions.[3] 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 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.

Finally, we study the mechanisms of these effects by combining the household-level data with macroeconomic data from national accounts and with individual-level data from additional surveys. This allows us to disaggregate effects by production factors, sectors, and skill levels and to differentiate between competing explanations for the distributional effects of the place-based policy. Beyond household incomes, we study effects on job creation, unemployment, investments, local rents and migration patterns.

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 groups are richer than the poorest decile groups 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 economic growth and 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

[2] We apply the EU's 'NUTS2' definition of a region. The median NUTS2 region in our sample has a population of 1.4 million.

[3] This empirical strategy builds on Becker et al. (2010) but is somewhat distinct from their approach.

about 1. Third, the place-based policy benefits 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 close to 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 and we examine three of those in this paper. First, they could benefit capital more than labor (Alder et al. 2016). Like a lot of place-based polices in advanced economies, a large share of the EU's regional funds takes the form of investment subsidies and tax credits. This kind of place-based support could directly increase returns on capital. Depending on the elasticity of substitution between capital and labor in supported firms, new capital investments could also substitute labor. Thus, place-based policies could increase the capital gains of firms more than their wage bill and, thereby, 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 and firms with capital-skill complementarities they could put upward pressure on high local wages without benefiting lower-income workers (Griliches 1969; Bartik 1991; Parro 2013; 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 examine these mechanisms by differentiating between production factors, sectors, and skill levels. Results from analyzing household data 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 more than it increases the incomes of less educated individuals. Evidence from surveys among beneficiaries in supported regions supports 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 and Saez 2014; Lakner and Milanovic 2016; Hammar and Waldenström 2021) with a focus on its spatial dimension (Aghion et al. 2019; Iammarino et al. 2019; Gaubert et al. 2021b). 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. Critically, we show that intra-regional inequality remains substantial and has become an increasingly important component of overall inequality in Europe in recent decades.

Second, we contribute to the literature on estimating economic responses to public spending. A key challenge in much of the earlier literature on "fiscal multipliers" is the lack of plausibly exogenous sources of variation in public spending (see Ramey (2011) for a review). A more recent development in this literature is the identification of multipliers based on public spending at lower levels of aggregation than the national government and this often allows for more credible identification strategies (e.g. Nakamura and Steinsson 2014; Acconcia et al. 2014; Corbi et al. 2019; Auerbach et al. 2020). We add to this strand of literature by combining comprehensive panel data on EU structural funds for more than 200 subnational units and over almost 30 years with both RD and DiD designs that rely on two distinct, plausibly exogenous sources of variation in public spending. In addition to estimating fiscal multipliers at the macro level, our data allow us to identify responses to public spending of household incomes at the micro level. The size of the multiplier that we estimate (1.0) is within the range of multipliers that most of these studies estimate (see Chodorow-Reich (2019) for a review).

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 2014b; Fajgelbaum and Gaubert 2020; Gaubert 2018; Gaubert et al. 2021a). These studies have so far abstracted from the welfare implications of intra-regional distributional effects of such policies. 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 et al. 2013; Kline and Moretti 2013, 2014a; Reynolds and Rohlin 2014), in Germany (Seidel and von Ehrlich 2018; Henkel et al. 2021; Siegloch et al. 2021), in the UK (Criscuolo et al. 2019) and in the EU (Becker et al. 2010, 2012, 2013, 2019; Ehrlich and Overman 2020; Blouri and von Ehrlich 2020; Dellmuth 2021). While there is no consensus on the effects of these policies (Dall'Erba and Fang 2017a), the bulk of these studies finds positive effects on overall growth, productivity, and employment. Our study supports these findings but goes beyond examining aggregate gains 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 is Reynolds and Rohlin (2015) who study inequality in US federal Empowerment Zones between 1994 and 2000.[4] Like our study, their research suggests that the policy increased inequality in supported areas. Compared to their paper, we study the effects of discretionary public funding and its mechanisms rather than tax incentives, focus on a substantially larger program over a longer period, 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 et al. 2013; Ehrlich and Overman 2020). 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 European Regions: Data and Stylized Facts

To study the distributional effects of place-based policies within regions, we require data on local incomes. To this end, 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 2017. 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 processing and, second, present key stylized facts and trends on inequality across and within European regions.

[4] A second exception is Albanese et al. (2023), who document that inequality in the Italian region of Molise declined after it lost access to EU funding.

2.1 Data

Definition of regions. Our definition of a European region follows the EU's NUTS2 geocode standard.[5] 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 place-based policy that we study is assigned at this level.[6] 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 supposed to be home to 0.8 – 3 million inhabitants.

Data sources. To measure the distribution of incomes within regions, we require household-level data with sufficiently fine-grained geographical identifiers. We collect such data from various sources. We use 86 national surveys that are compiled by the Luxembourg Income Study (LIS) and provide data for regions in Austria, Estonia, Greece, Hungary, Ireland, Italy, Lithuania, Poland, Sweden, and Slovakia (Luxembourg Income Study 2023). We complement this information with data from national household surveys provided by the EU's Statistics of Income and Living Conditions (EU-SILC). 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 (Eurostat 2020). Third, 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 geocodes. 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 (University of Essex 2020); for Germany we use the Socio-Economic Panel (SOEP) (DIW 2020).

Data harmonization. In each of the 260 household surveys that we collect, we apply the same approach. First, in order to assign households to NUTS2-regions, we harmonize the geographic identifiers of the surveys according to the NUTS2 definition of 2016, taking into account all administrative reforms in the observation period. To compare incomes across households of different sizes, we apply the "square root scale" and divide household incomes by the square root of household members. To compare incomes across countries and over time, we adjust them to 2011 international dollars

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

[6] 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.

at purchasing power parity (PPP). 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 $N = 1034$. To address the concern that small samples distort aggregate measures, we exclude region-year-specific measures that are based on less than 50 respondents in the baseline.[7] Any time-invariant differences of data sources and survey methodologies across countries are absorbed by country-fixed effects, which are included in each regression. A detailed description of the data sources and the steps we took to collect, harmonize and process the data can be found in Appendix A.1.

Validation of data quality. In Appendix A.2, we check the quality of the household-level data when aggregated to the regional level. We find plausible geographic patterns and strong correlations between our computed regional mean of household incomes and regional GDP statistics from national accounts.

Income measures. Our main income measure is disposable household income, i.e., the income that households 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 and all surveys that we use include this standard measure and apply the same definition for calculating it. For examining mechanisms and robustness, we also use alternative income concepts such as total income, labor income, capital, and transfer income. We describe these in Section 5 below. For all income concepts, we calculate mean incomes, mean incomes for the ten decile groups by disposable incomes, incomes at various region-specific percentiles, percentile ratios (P90/P10, P80/P20), and Gini coefficients for a total of 3,772 region-year observations.

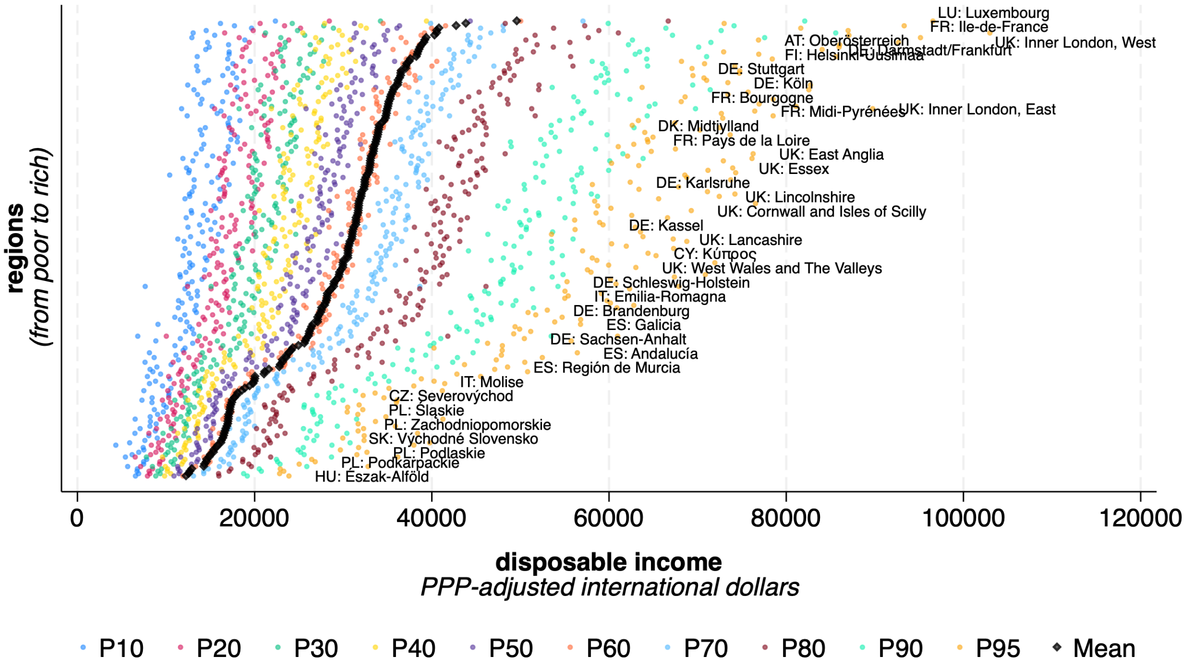
2.2 Stylized Facts on Regional Inequality in Europe

These new data allow us to analyze inequality in Europe from new perspectives. Critically for our research question, we can examine inequality within regions and, at the same time, compare different income percentiles across regions in the EU. While Appendix A.3 provides a detailed exploration of this new data set, the following discussion concentrates on the patterns that are most relevant for the main research question of this study.

First, inequality within regions is substantial. Figure 1 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 include Luxembourg, the greater Paris area ("Ile-de-France"), London, and regions in Southern Germany. Among the poorest regions with data are regions in Poland,

[7] Appendix D.5 shows that the results do not depend on this choice.

Figure 1: The income distribution within European regions



Note: Annual equivalized disposable household income of various percentiles of the intra-regional income distribution, latest available year.

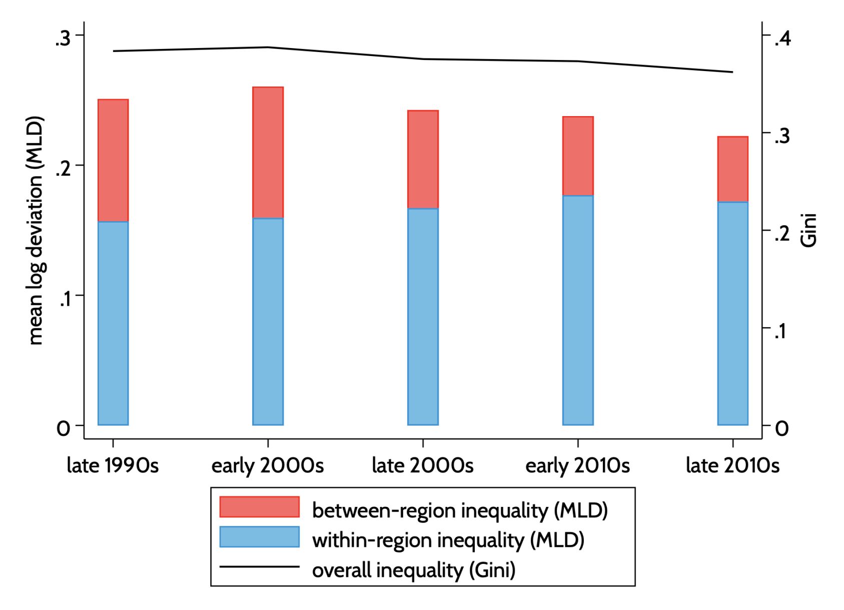
Hungary, Southern Italy, and the Baltics.[8] These data confirm the well-known fact that inequality between European regions is substantial. Mean disposable household incomes in the richest regions exceed those in the poorest regions by a factor of 4. More importantly for our research question, however, the data also shows the large spread of incomes *within* regions. Even in the richest regions, many people have a lower disposable income than the median in relatively poor regions. 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 well-off. Hence, place-based policies that redistribute resources from richer to poorer regions do not necessarily help poor households and might benefit the relatively rich. Whether this form of redistribution is progressive crucially depends on its distributional effects within regions.

A second important fact is that over time, inequality within regions increases relative to inequality between regions. To analyze how the two dimensions of inequality have developed, we decompose total European inequality into these two components. For this purpose, we require an additively decomposable inequality measure and choose the mean log deviation (MLD or GE(0)).[9] In Figure 2 we use this measure to plot

[8]Note that data for regions in Romania and Bulgaria are missing.

[9]See Lakner and Milanovic (2016); Hammar and Waldenström (2021) for similar decompositions of *global*

Figure 2: Decomposing European inequality between and within regions



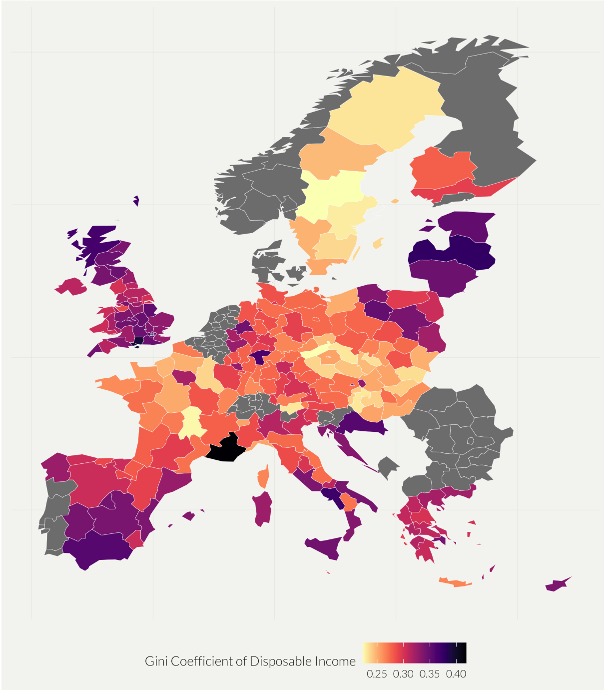
Notes: The figure plots the between-region component and the within-region component of European inequality. Each regional distribution is represented by 10 deciles groups. The height of the bars indicates the level of inequality as measured by the mean log deviation (MLD or GE(0)). To ensure comparability over time, the sample of regions for this exercise is fixed; regions in countries that joined the EU later and regions with missing data are not included.

the evolution of the between-region and the within-region component of European inequality between the late 1990s and the late 2010s. 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. Crucially, the graph shows that inequality within NUTS2-regions contributes more to European inequality than inequality across these regions. Furthermore, while inequality across these regions has declined somewhat over time, within-region inequality has slowly increased over the last 25 years.

To conclude this section, we visualize the geographic variation of inequality within regions in Figure 3. Regional Gini indices average at around 0.30 and are thus similar in size to the national Gini indices of European countries. The most unequal region in the EU is Provence-Alpes-Cote d'Azur in France with a regional Gini of 0.40. This is likely to reflect income differences between a rich coast (St. Tropez, Cannes, Nice) and a poorer, rural hinterland. The most equal region is Severozapad in Czechia with a regional Gini of 0.22. More generally, regions in more unequal countries (e.g., UK) tend to be more unequal than regions in more equal countries (e.g., Sweden). However, there are also important differences within countries. For instance, in both Spain and Italy, southern regions are substantially more unequal than northern regions.

inequality into its between-country and within-country components.

Figure 3: Intra-Regional Gini indices



Notes: The map shows intra-regional Gini indices of equivalized disposable household income for the latest available year.

3 Research Design: The European Structural and Investment Funds

3.1 Institutional Background

The EU administers the world's largest place-based policy. For the 2021-2027 funding period, it agreed on structural and investment funds worth 392 billion euros or 56 billion euros annually. 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)).[10] A wide range of private-sector and public-sector projects that promise to promote economic development are eligible to receive such funds. Eligible organizations – mostly private firms, public bodies and voluntary organizations – must submit project applications that meet the selection criteria of specific 'operational programs' and will then receive financial support with a maximum co-financing rate of up to 85 percent.

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).[11] The ERDF is advertised as aiming to "strengthen economic, social and territorial cohesion in the EU by correcting

[10]The volume of place-based policies in China is substantially smaller (Lu et al. 2019).

[11]In addition, 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.

imbalances between its regions."[12] The official headline goal of the ESF is to "improve the situation of the most vulnerable people at risk of poverty"[13] 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. A map in the Appendix (Figure A.7) gives an impression of the volume of these funds by visualizing the per capita amounts disbursed to individual regions between 1989 and 2017. As can be seen, these are non-trivial amounts. Multiple regions have received more than EUR 10,000 per inhabitant since the 1990s. 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 (2014a) 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 (2014a: 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.

3.2 Identification I: Regression Discontinuity Design

We are interested in the effect of EU funds on income growth (Δy) for all decile groups d of the intra-regional income distribution D within regions r in year t:

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

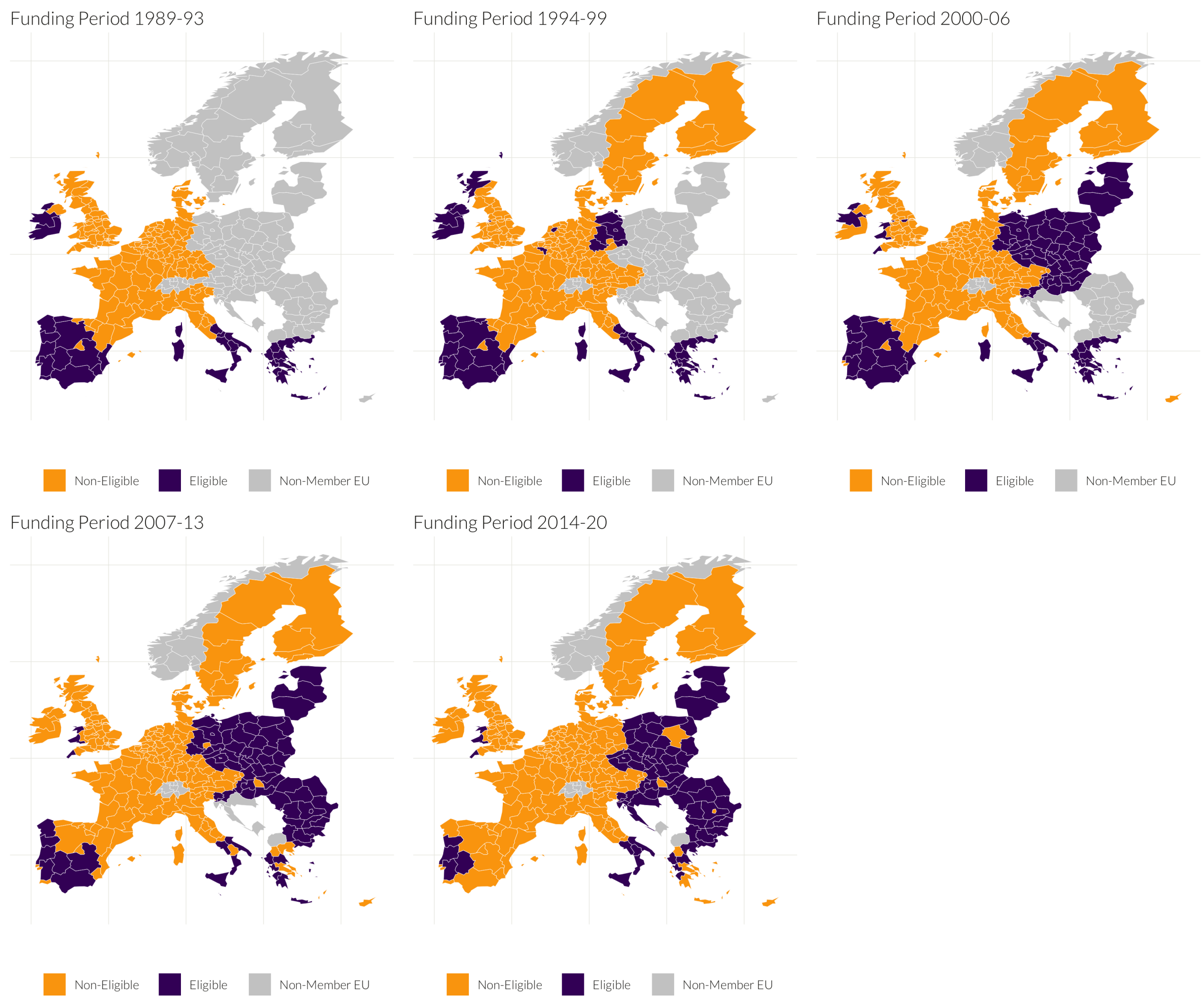
A natural expectation is that EU funds are not allocated independently of regional income growth. As the stated goal of EU structural funds is to promote the cross-regional convergence of incomes it is plausible that regions with weaker growth prospects are more likely to receive a larger amount of funding, which would bias naïve estimates of β downward. It is, however, equally plausible that policymakers allocate more funds to regions with better growth prospects to demonstrate their effectiveness. In this case, estimates of β would be biased upward. In sum, there are reasons to expect an endogenous relationship such that $\mathbb{E}(funds_{rt}, \varepsilon_{drt}) \neq 0$.

To take the potentially endogenous allocation of EU funds into account we rely on a discontinuity in the allocation of EU funds across regions and over time. Although allo-

[12] https://ec.europa.eu/regional_policy/en/funding/erdf/
[13] https://ec.europa.eu/regional_policy/en/funding/social-fund/

cation rules in the observation period (1989-2017) changed, one feature characterized 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 others. 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 labeled as regions belonging to "Objective 1" (1989-2006), the "Convergence Objective" (2007-2013), or to the set of "less-developed regions" (2014-2020). While labeling varied over time, the rule that such regions receive the largest per capita amounts has remained in place from 1989 onward until the time of writing. Figure 4 plots eligible regions over time. While many regions stayed within their respective funding category, others changed their eligibility status over time. This allocation rule allows us to implement a regression discontinuity (RD) design that leverages both the cross-sectional and the over-time variation visible in the figure. In section 6, an alternative difference-in-differences (DiD) design isolates the time dimension.

Figure 4: Eligibility over time



Our RD approach is similar to previous research that also relied on this discontinuity (Becker et al. 2010, 2019) but differs along several dimensions. First, we follow existing research in using a region's *eligibility* status as the treatment variable in the baseline analysis but extend this by using newly available data to define the treatment as the actual amount of disbursed flows to a given region. The variable *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 in yeat t 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 et al. 2010, 2013, 2019). As the data show, the amounts of disbursed funds differ across regions with the same eligibility status (see Figure 8 and Figure A.7 in the Appendix). Data on actual disbursements in year t, thus, add valuable information on the intensity of the treatment and compliance with the intention to treat (ITT).[14]

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 unavailable to existing research. Instead, scholars have used more recent GDP data from other sources to reconstruct the historical forcing variable.[15] Because of data revisions and differences in methodologies, however, the data series differ substantially, leading to an incorrect mapping from the forcing variable to the treatment assignment. As a result, scholars find highly imperfect compliance with the 75-% rule.[16] Through direct correspondence with staff of 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.[17] 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 para-

[14] Several 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 2017b). Most EU payments are reimbursements and are thus made *after* the actual expenditure. Studies like ours that are interested in the immediate economic effects of expenditures would be distorted if they considered the timing of the reimbursements rather than the timing of the expenditure. Information on the latter was so far not available. The new data we use include information on the timing of the expenditure.

[15] Scholars have typically used data from Cambridge Econometrics (Becker et al. 2013).

[16] See, for instance, Figure 1 in Becker et al. (2019).

[17] 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 A.2 in the Appendix.

metric approaches with high-order polynomials can produce noisy estimates. Calonico et al. (2014, 2017) 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 Cunningham (2021) over the *global* approach that the existing literature on EU funds implements (see, e.g. Becker et al. (2019); Borin et al. (2021)). We follow these recommendations and implement the approach proposed by Calonico et al. (2014) via the RDROBUST package (Calonico et al. 2017).

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

$$\Delta y_{rtd} = \beta_d a_{rt} + \gamma f(gdp^{EU}_{rt}) + \mu_c + \tau_t + \epsilon_{rt}, \quad \forall d \in D \tag{2}$$

where the binary variable $a_{rt} = 1_{(gdp^{EU}_{rt} > 75)}$ indicates observations above the eligibility cutoff. The function $f(.)$ includes local linear polynomials of gdp^{EU}_{rt} with different slopes above and below the cutoff. The sample for the local linear regressions is restricted to observations that satisfy $\mid gdp^{EU}_{rt} - 75 \mid < h$, 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. $D = \{1, 2, 3, \ldots, 10\}$ is the set of decile groups d of the intra-regional income distribution. In the RD logic, controlling for local polynomials of gdp^{rt}_{EU} 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 ITT at the cutoff.

In addition to estimating the sharp RD model specified in equation 2, 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 2:

$$T_{rt} = \phi a_{rt} + \zeta f(gdp^{EU}_{rt}) + \mu_c + \tau_t + \varepsilon_{rt} \tag{3}$$

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

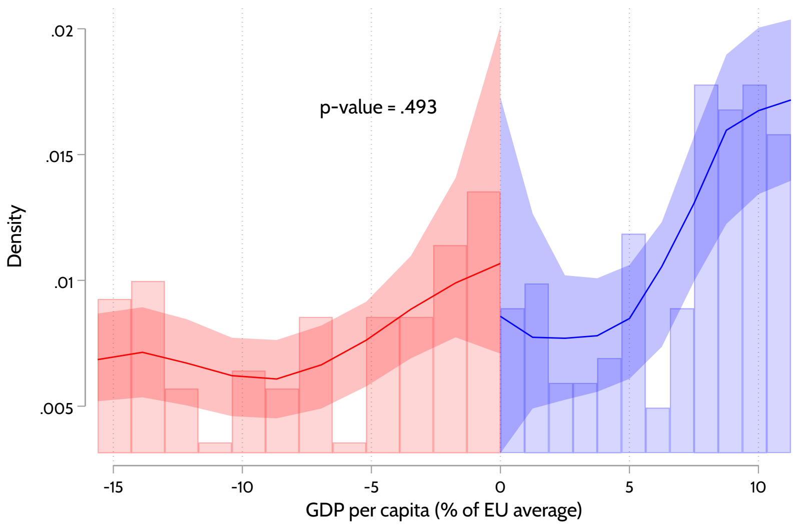
Here, T is either defined as the binary treatment variable *eligible*, or the continuous treatment variable *funds*. Regions are coded as *eligible* if they are classified as belonging to "Objective 1", "Convergence Objective", or to "less-developed regions" in the official EU documents and thus qualify for the largest volumes of EU funds (see Figure 4). The continuous variable *funds* is defined as yearly disbursements of EU funds as a share of regional GDP (see Figure A.8 for a map that visualizes disbursements across regions). 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.

3.3 Threats to Identification: RD

The validity of this RD design rests on two key assumptions, which we challenge with two types of tests.

Manipulation Test. First, an immediate threat is the possibility that NUTS2-regions are self-selecting into EU funding (sorting). Previous research has extensively argued and shown that this is not the case (Becker et al. 2010, 2012, 2013). NUTS2-regions are unlikely to be capable of influencing their GDP to the degree that they can reliably sort themselves just below the 75% EU average. Deliberate sorting also would require member states to accurately predict the EU's overall GDP before submitting national statistics. As GDP forecasts come with substantial uncertainty, this is unlikely. Also, misreporting of GDP figures is difficult to implement within the democratic settings of EU member states. Furthermore, we directly test whether there are significant discontinuities in the density of observations around the cutoff with the help of local polynomial density estimation (Cattaneo et al. 2020). We plot the result of this test in Figure 5. As is visible, there is no statistically significant jump around the 75% cutoff, adding further support to the assumption that sorting is unlikely in the setting.

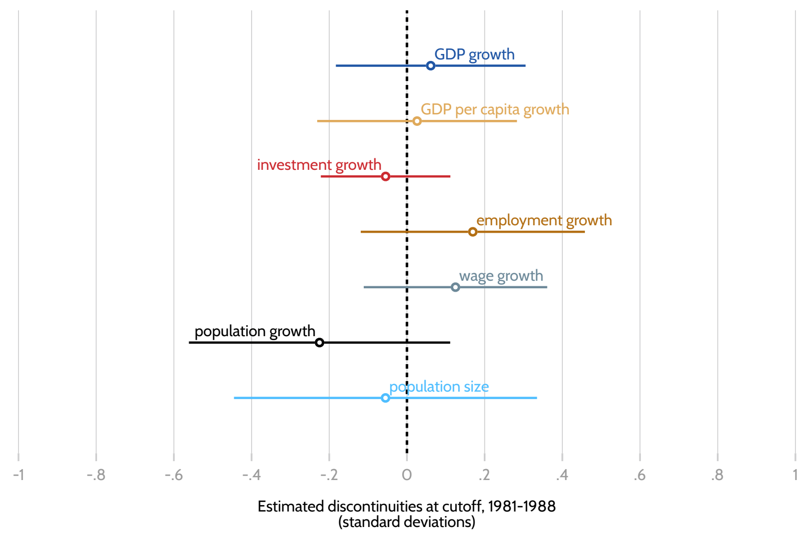
Figure 5: Manipulation test



Notes: The manipulation test is based on a local polynomial density estimation implemented with the RDDENSITY package by Cattaneo et al. (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 0.493 (jackknifed robust standard errors).

Pre-treatment Placebo Test. 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 Eurostat and Cambridge Econometrics: GDP growth, GDP per capita growth, investment growth, employment growth, wage growth, population growth, and population size. If the treatment is truly randomized locally, 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. Reassuringly, there are no discontinuities in pre-treatment characteristics. 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 in 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 2 and Table 1) but use pre-treatment variables as outcomes. All outcome variables are z-score standardized such that estimated coefficients indicate the size of the discontinuity in standard deviations. 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

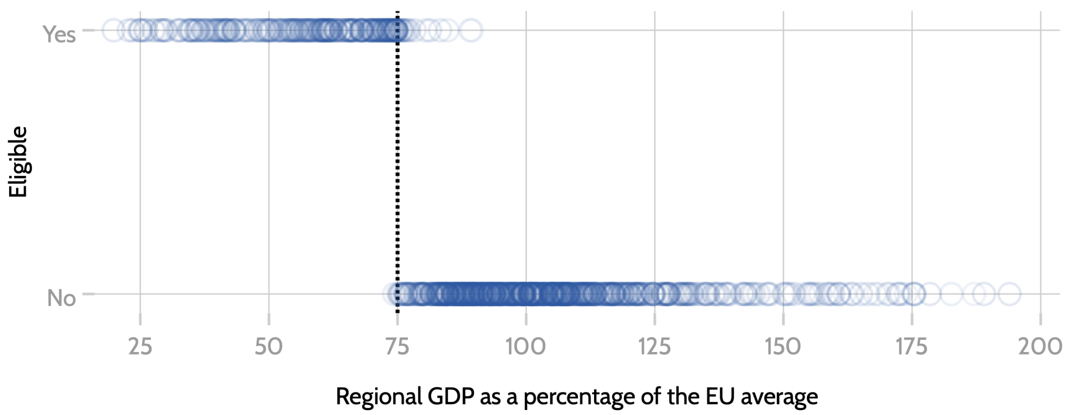
This section presents the main results of estimating the effect of the place-based policy on incomes and their distribution within regions by means of the RD design described in the previous section.

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.

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.[18] 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 (Appendix D.3), and b) estimate a "donut" RDD, which excludes all observations close to the cutoff (Appendix D.4). All these approaches yield the same results because there are few exceptions and because the compliance with the institutional rule is strong.

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 – the RD forcing variable – on the x-axis.

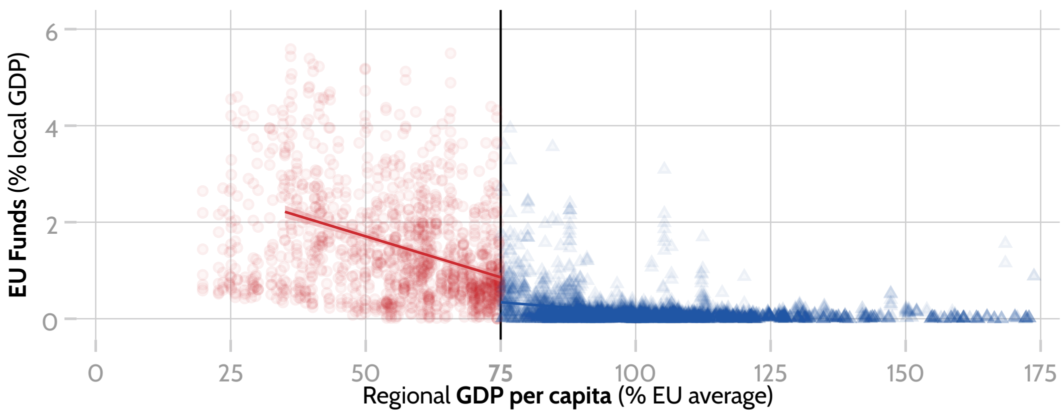
Next, Figure 8 plots the actual disbursements that a region receives in a given year as a function of the forcing variable. Here, compliance is naturally fuzzier. It is clearly shown that regions above the 75%-cutoff receive less funding than those below the cutoff, but disbursements do not drop to zero above the cutoff. There are various reasons for disbursements to regions above the cutoff: a) According to the EU's rules, eligibility for funding 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

[18] 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 A.2 in Appendix D, we describe these exceptional cases one by one.

EU implemented several exceptional rules and transition funds for regions that lost their eligibility status;[19] d) there are disbursements to the 15 exceptionally eligible regions discussed above. Nevertheless, the drop in funding volumes at the cutoff is substantial.[20]

We estimate the size of this drop in disbursements at the cutoff with the help of the local linear RD regressions, specified in equation 2, and plot results in Figure 9. Overall, the drop is statistically significant for all bandwidths except the extremely small ones. 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, because the sample in these small bandwidths is very small 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. As a significant first-stage effect on funding disbursements is necessary to observe any potential economic effect, we study these effects with all bandwidths $h \geq 20$. The baseline analysis is based on the moderate bandwidth of $h^{\star} = 40$, which allows us to show results for the full range of bandwidths between $\frac{h^{\star}}{2} = 20$ and $2h^{\star} = 80$ in robustness regressions.[21] These robustness tests are reported in Appendix D.1 and show that results hold for the full range of these alternative bandwidths.

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 and their 95% confidence intervals is 40.

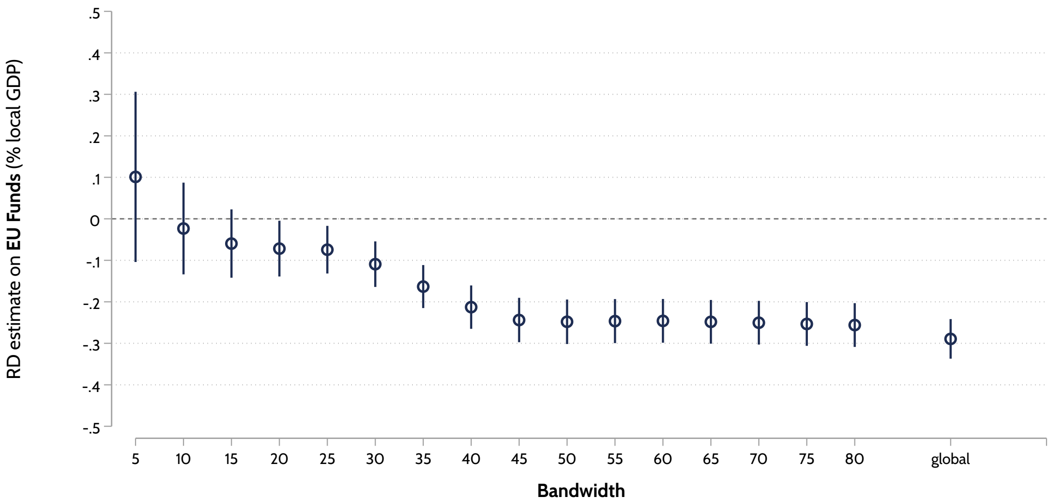
All in all, the analysis of the first-stage effect suggests that the place-based policy complies with the institutional rule used for the identification. The subsequent analysis of the policy's economic effects will use sharp RD methods to estimate the ITT of

[19]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).

[20]We also estimate the discontinuity for *EU funds per capita* and find a drop of 34 euros per capita.

[21]The sample in a bandwidth of $h = 80$ is close to the global sample.

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



Notes: Coefficient plot of local linear bias-corrected RD estimates with robust nonparametric standard errors, clustered at the NUTS2-level, based on equation 2. The regressions use a triangular kernel and varying bandwidths. Outcome variable *EU funds (% GDP)*. 95% confidence intervals.

crossing the cutoff and fuzzy RD methods to estimate the LATE of eligibility as well as actual disbursements.

4.2 Economic Growth and Household Incomes

The analysis now turns to estimate 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 on different measures of average incomes.

Table 1 shows effects on growth rates of regional GDP per capita from national accounts in 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 statistically significant at the 1%-level. This result is similar to previous results in the related literature (Becker et al. 2019).

Column 2 turns to our new 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 capture a similar variation in incomes as GDP data from national accounts. This holds true even

Table 1: Income Growth

Intention-to-Treat Effect (Sharp RD)	GDP per capita	Household income
Above cutoff (75%)	-0.35	-0.43
	(0.09)	(0.14)
Country FE, Year FE	✓	✓
Observations (above/below cutoff)	1267/3171	797/1638

Local Average Treatment Effect (Fuzzy RD)	GDP per capita	Household income
Eligibility	0.49	0.50
	(0.11)	(0.16)
Country FE, Year FE	✓	✓
Observations (above/below cutoff)	1266/3135	797/1638

Notes: The table reports local linear bias-corrected RD estimates with robust non-parametric standard errors, which are clustered at the NUTS2-level and reported in parentheses. All regressions use a *triangular kernel* and an RD bandwidth of *40*. The forcing variable is *GDP per capita as a share of the EU average*. The top panel reports *sharp* RD estimates and the bottom panel reports *fuzzy* RD estimates, with official *eligibility* as the treatment.

though the sample that can be used for this analysis is substantially smaller than the sample for the analysis based on national accounts data. The results also highlight that the regional increases in economic growth promoted by the policy translate into higher incomes at the level of households.

In Appendices D.1, D.2, D.3, and D.4, we show that these results are robust to alternative RD bandwidths, to using a uniform instead of a triangular RD kernel, and to estimation in alternative samples.

4.3 Fiscal Multipliers Estimates

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 place-based spending.

We follow standard notation in the related literature (e.g., Kraay 2012; Chodorow-Reich 2019) 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 a 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 baseline bandwidth.

All three estimates point to a fiscal multiplier close to 1.0 and statistically not different from this value. This suggests that the policy's redistribution of resources across European regions neither increases nor decreases aggregate output in the European Union.

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's (2011) 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's (2019) 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 et al. (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 *nonparametric* results are local linear bias-corrected RD estimates with robust nonparametric standard errors estimated with a triangular kernel as in Table 1.

4.4 Inequality Within Regions

Having provided evidence on the positive *aggregate* effects of EU funds on incomes, we now turn to answering this study's main research 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).[22] 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.

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%)	-0.129	-0.064	-0.012	-0.010
	(0.027)	(0.011)	(0.005)	(0.004)
Country FE, Year FE	✓	✓	✓	✓
Observations (above/below cutoff)	832/1729	801/1686	801/1686	798/1686
Local Average Treatment Effect *(Fuzzy RD)*				
	Gini Coefficient	P90/P10 ratio	P80/P20 ratio	Coefficient of Variation
Eligibility	0.156	0.075	0.015	0.012
	(0.031)	(0.013)	(0.005)	(0.005)
Country FE, Year FE	✓	✓	✓	✓
Observations (above/below cutoff)	832/1729	801/1686	801/1686	798/1686

Notes: The table reports local linear bias-corrected RD estimates with robust nonparametric standard errors, which are clustered at the NUTS2-level and reported in parentheses. All regressions use a *triangular kernel* and an RD bandwidth of *40*. The forcing variable is *GDP per capita as a share of the EU average*. The top panel reports *sharp* RD estimates and the bottom panel reports *fuzzy* RD estimates, with official *eligibility* as the treatment. Outcome variable: year-on-year differences of various inequality measures.

A year of eligibility for the policy increases the local Gini coefficient [0, 100] by about 0.16 points. This is equivalent to 4 percent of a standard deviation per year of eligibility ($mean_{gini} = 30.62$; $sd_{gini} = 3.68$). The ratio of household income of the 90th percentile relative to the 10th percentile increases by 7.5 percentage points (10 percent of a standard deviation, $mean_{P90/P10} = 3.98$; $sd_{P90/P10} = 0.74$), the effect size on the P80/P20 ratio is 1.5 percentage points (5 percent of a standard deviation, $mean_{P80/P20} = 2.44$; $sd_{P80/P20} = 0.30$), the effect size on the coefficient of variation is 1.2 percentage points (5 percent of a standard deviation, $mean_{CV} = 0.66$; $sd_{CV} = 0.23$). These coefficients are all statistically significant at the one-percent level. As before, the top panel of the table shows the ITT estimated by sharp RD while the bottom panel shows the LATE of eligibility estimated by fuzzy RD. Appendix D shows that these results are robust to a wide range of alternative specifications, including alternative bandwidths and RD

[22]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 the most weight on the right tail. All measures are positively correlated and indicate the inequality of disposable household income within regions.

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. In the next section, we examine the mechanisms behind this effect and study distributional effects across income groups, factors of production, sectors, and skill levels.

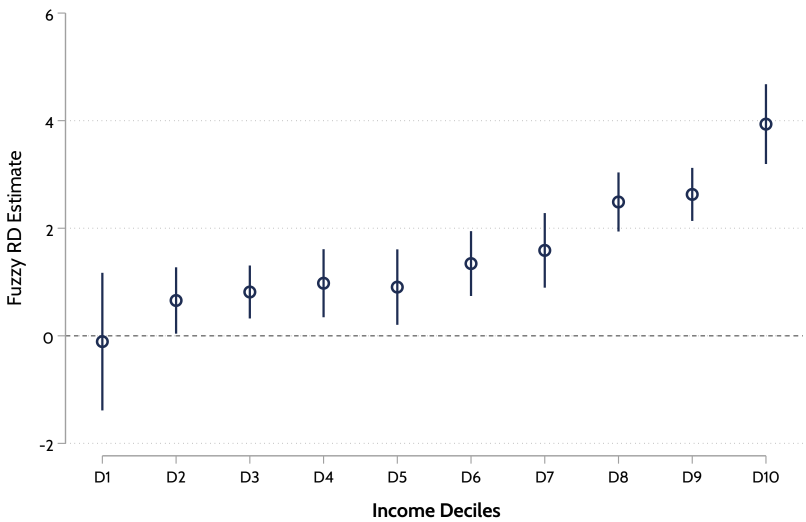
5 Distributional Effects and Mechanisms

5.1 Distributional Effects Across Income Groups and Factors

To examine the mechanisms and distributional effects behind this increase in inequality within regions, we, first, attribute the households of each region to ten equally sized decile groups based on the intra-regional distribution of disposable household income. For each decile group in each region and each year, we then compute the growth rates of the most important income types, differentiating between income derived from *labor*, *capital* and public *transfers*. Appendix B.1 describes these measures in detail.

In models that repeat the baseline fuzzy RD specifications of the growth regressions in Table 1, we first estimate the effect of the place-based policy on the decile-group-specific growth of *total* (*labor* + *capital* + *transfer*) gross income. Figure 10 plots the results of these ten regressions as a coefficient plot. The results uncover a clear pattern. Increases in total gross income are strong and statistically significant for households at the top of regional income distributions, small for those at the bottom and insignificant for the poorest ten percent.

Figure 10: Effects on total income by regional decile

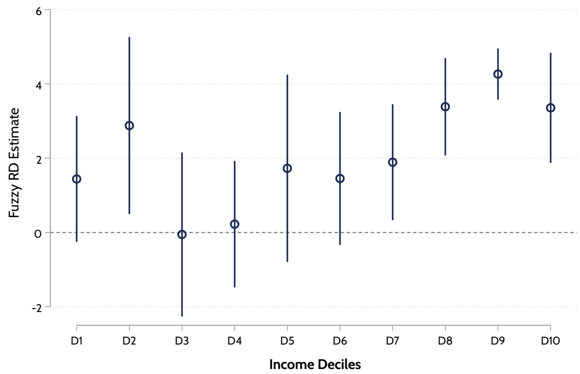


Notes: Fuzzy RD regressions as in Table 1. Outcome variable: annual growth of total income by regional decile-group. Plotted are estimated effects of the treatment variable *eligibility* along with 95% confidence intervals.

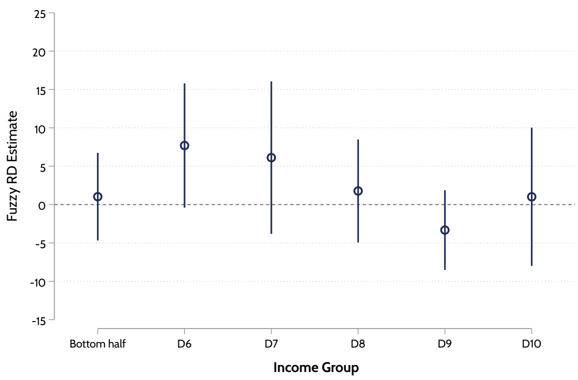
Figure 11 shows the results for differentiating between the three main sources of gross income. This disaggregation naturally leads to less precisely estimated coefficients, especially for decile groups in which only few households receive a given type of income. (The poorest households in Europe receive mostly transfer income, only little labor income and almost no capital income.) Nevertheless, the disaggregation clearly shows which income type is responsible for the distributional pattern identified above: The place-based policy increases wages primarily for upper-income groups. Panel (a) shows increases in labor income growth for households in the top 40 percent of the regional income distribution by 2-4 percentage points. With the exception of an imprecisely estimated coefficient for the second decile group, effects for the bottom 60 percent are smaller and not distinguishable from zero at conventional levels of statistical significance.

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

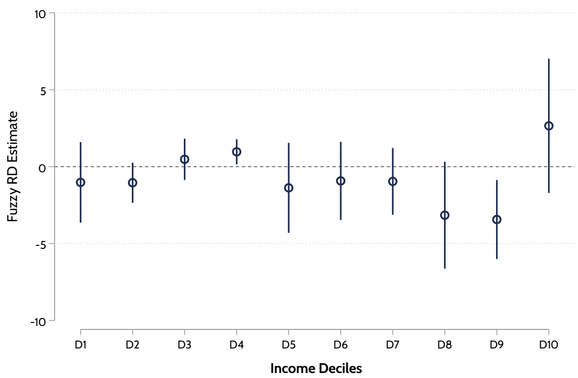
(a) Labor Income



(b) Capital Income



(c) Transfer Income



Notes: Fuzzy RD regressions as above in Table 1. Outcome variables: annual growth of capital gains **(a)** and income from public transfers **(b)** by regional decile group. 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.

An alternative mechanism through which EU funds increase inequality could be that they disproportionally increase capital gains by affluent capital owners.[23] When applying the analogous approach for income derived from capital in Panel (b), we do not find significant effects for any income group. The effect on total capital income growth is also statistically indistinguishable from zero. EU funds thus appear not 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, money is fungible and governments might substitute their local investments with EU funds and use the newly available funds to increase transfers. When testing this hypothesis in Panel(c), the results for public transfers do not point to such an effect. Instead, nine of ten coefficients are not statistically significant. While the statistically significant negative result for the 9$^{\text{th}}$ 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 a substantial amount of public transfers.[24]

In sum, these results suggest that EU funds increase inequality by promoting labor incomes of those at the upper end of regional income distributions while labor incomes of the least well-off are not significantly affected. Changes in the distribution of income *across factors*, however, 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 point to larger capital gains than wage gains, as capital owners on average have higher incomes. Instead, distributional effects *within* the factor labor increase the wages of relatively rich workers more than those of workers with lower incomes.

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

[23] Alder et al. (2016) find that special economic zones in China increased GDP mainly through a positive effect on physical capital accumulation.

[24] One limitation of our analysis is that we do not observe the utility that different households derive from public spending. It could mitigate the policy's inegalitarian effect if poorer households benefit more from public spending and services than rich households (Aaberge et al. 2019). While our approach does not allow us to examine this question directly, the finding that a substantial share of spending reaches the private sector should attenuate this potential concern.

5.2 Distributional Effects Across Sectors: Macro-level Evidence

To answer this question, we turn to macro data from national accounts and initially examine the extent to which EU funds spur investments across economic sectors.[25] 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 and positive effect of EU funds on overall investment (gross fixed capital formation). Eligibility for the place-based policy increases investment growth by 1.5 percentage points.

Table 4: Investments by Sector

	DV: Growth rate of investment by sector						
	all sectors	public sector	industrial sector	service sector	construct. sector	financial sector	agricultural sector
Eligibility	0.015	0.051	0.031	0.028	0.080	0.009	0.014
	(0.004)	(0.005)	(0.013)	(0.012)	(0.019)	(0.006)	(0.006)
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 as in Table 1. Outcome variables: annual growth rates of regional investment across sectors (see top row).

The remaining columns differentiate by investments in different sectors. Positive effects are found in almost all sectors. As might be expected, the largest effects are observed in the construction sector: EU funds often finance infrastructure projects or support firms in building new facilities. Relatively large effects are also observable in the public sector. Public agencies often receive EU support for local investments in public infrastructure. The industrial and the services sector also see a substantial increase in investment as a result of increased place-based support from the EU. The smallest effects are recorded for the financial and agricultural sectors, which are not explicitly targeted by the policy. More generally, the evidence does not support the view that place-based funding is biased towards high-wage sectors. As the table's second to last row shows, both low-wage and high-wage sectors benefit from the policy. Hence, unequal distribution across sectors does not explain the policy's inequality-increasing effect.

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-on-year changes as outcome variables in the regressions reported in Table 5. Column

[25] Aghion et al. (2015) and Liu (2019) explain why the effectiveness of industrial policy may differ across sectors.

1 shows that EU funds lead to a significant increase in the 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. An exception is the industrial sector, where additional investments do not seem to cause statistically significant increases in employment. A negative effect on agricultural employment suggests that the policy contributes to the structural change from farm to non-farm 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	construct. sector	financial sector	agricultural sector
Eligibility	0.169	0.061	-0.003	0.047	0.054	0.049	-0.040
	(0.045)	(0.011)	(0.008)	(0.014)	(0.012)	(0.006)	(0.008)
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 as in Table 1. Outcome variables: year-on-year differences of employment rates across sectors.

Table A.3 in the Appendix 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 rate or the youth unemployment rate are considered the policy is estimated to reduce local unemployment rates significantly and substantially.

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, our 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. [26] We examine the hypothesis that the place-based

[26] 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 Hecksher-Ohlin (Stolper and Samuelson 1941)) and sectors (à la Ricardo-Viner), the recent literature emphasizes unequal effects of trade across heterogeneous firms that differ in the skill-level of their employees (à la Melitz (2003)).

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 place-based funding, firms that employ high-skilled workers may be in a superior position to access the funds. Second, firms with high-skilled employees tend to be more productive. They might then have an advantage when it comes to paying 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 behind this 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. Fourth, if there is capital-skill complementarity for at least some types of physical capital (Griliches 1969; Duffy et al. 2004; Parro 2013), EU funds that spur investments in such capital benefit high-skilled workers relatively more than low-skilled workers.

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 previously. These data include individual-level information on educational background, which we harmonize across national surveys. We code as low-skilled individuals with lower secondary education (*ISCED2*) and less and as high-skilled individuals with upper secondary education (*ISCED3*) or more. Based on these measures, we then classify individuals as low-skilled or high-skilled. For each education group in each region and in each year, we calculate the annual growth rate of the group's labor income. In order not to distort the measure by including individuals with different skill levels that are too young or too old to work, we consider each region's working-age population alone for this exercise.

In Table 6, we use these education-specific growth rates of labor income as dependent variables. We find positive effects for both groups but the strongest effects are estimated for the high-skilled individuals within regions. Funding eligibility increases the income growth of high-skilled workers by more than 3 percentage points. The effect on the labor incomes of low-skilled workers is estimated at less than 2 percentage points. The estimated effect on the difference between the growth rates ($\Delta_{high-low}$) is statistically significant at the ten percent level ($p = 0.065$). As the bottom row of the table shows, average labor incomes of the highly educated are more than twice as large as those of the poorly educated in the EU.

In sum, these results help explain the unequal effects of the place-based policy. The income gains are strongest for high-skilled workers. As these have higher incomes on average than low-skilled workers, inequality within supported regions increases.

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

	DV: Growth of labor income		
	Low Education		High Education
Eligibility	1.965		3.090
	(0.673)		(0.340)
$\Delta_{high-low}$		1.125	
		(0.610)	
Country FE and Year FE	✓		✓
Observations	502/492		502/492
Mean labor income	9963		20669

Notes: Fuzzy RD regressions as in Table 1. Outcome variables: growth of disposable personal income of individuals aged 24-65 by level of education.

5.3.1 Probing the Mechanism: Survey Evidence

To further probe this mechanism, we turn to an alternative empirical strategy and another type of data. Rather than estimating the effect of the policy on incomes, we rely on surveys that directly ask respondents in supported regions whether they personally benefited from the policy. The data come from Borz et al. (2022) who surveyed 8,559 respondents in 17 European regions (the sample includes a minimum of 500 respondents per region).[27] The surveys include regions below the 75%-threshold that receive a large amount of funds as well as regions that receive very little support.[28] In addition to asking respondents whether they personally benefited from the funds, the survey also collected information on their socio-economic characteristics and their knowledge of and attitudes toward EU policies.

In Table 7, we use these data in OLS regressions, where the outcome variable is a binary indicator for respondents who state that they *personally benefited from the policy*. All regressions control for whether respondents report that they *know about the policy* such that we only compare reported personal benefits from the policy across individuals with the same knowledge of the policy.[29] Gender, age, employment in the agricultural sector and political ideology are also controlled for. Column 1 shows that individuals with higher incomes are more likely to respond affirmatively. Column 2 and the marginal-effects plot in Figure 13 shows that this association depends on the actual flow of funds to the respondent's region is only observable in regions that receive a substantial amount of funds. Such a heterogeneity would not be observed if the results only captured a generally larger satisfaction with EU policies among richer

[27] 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 Northeast England.

[28] The Hungarian region of Nyugat-Dunantul received more than EUR 3000 per capita in the 2007-2013 funding period, while the German region of Baden-Wuerttemberg received EUR 18 per capita in the same period.

[29] *Heard of ERDF* and *Heard of ESF* are binary variables that indicate individuals who report that that they have heard about these two main elements of the EU's place-based policy.

respondents. Guided by the results on the skill bias of the place-based policy as a mechanism, columns 3 and 4 repeat the same analysis with education as the explanatory variable. The pattern is the same as for income, supporting this mechanism.

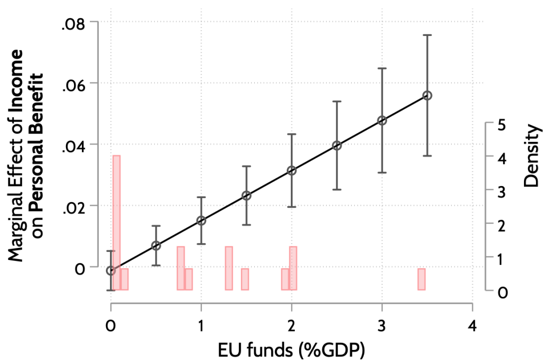
To be sure, endogeneity bias cannot be ruled out, but the results are neither driven by political ideology, a better knowledge of the policy or a generally larger satisfaction with EU policies among the richer and better-educated. While they thus provide no causal evidence, the associations in the survey data align well with the findings that richer and better-educated individuals benefit more from the place-based policy.

Table 7: Self-reported Personal Benefit

	(1)	(2)	(3)	(4)
Income	0.013	-0.001		
	(0.005)	(0.003)		
× EU funds		0.016		
		(0.003)		
Education			0.026	0.018
			(0.003)	(0.003)
× EU funds				0.008
				(0.003)
Heard of ERDF	0.127	0.126	0.114	0.114
	(0.020)	(0.020)	(0.020)	(0.020)
Heard of ESF	0.100	0.099	0.096	0.096
	(0.012)	(0.013)	(0.012)	(0.012)
Controls	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Regions	17	17	17	17
Observations	8451	8451	8451	8451

Notes: OLS regressions. Outcome variable: Binary indicator for respondents who state that they "personally benefited" from a project funded by EU funds. Standard errors, robust to clustering at the NUTS2-level, in parentheses. Controls include *gender*, *age*, *employment in the agricultural sector* and *political ideology*.

Figure 13: Marginal Effects



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 column 2 of Table 7. 95% confidence intervals.

5.4 Alternative Mechanisms

Spatial Distribution within Regions. In Appendix C.2, we examine whether the spatial distribution of funds within regions could explain the inequality-increasing effects (Table A.4). To do so, we differentiate between households in rural and urban areas. Urban areas are richer by about 10 percent in the regions we examine. If the place-based funds were biased toward urban areas, this could explain the larger income gains for richer households. The results, however, show that effect sizes are very similar in rural and urban areas.

Migration. Another possibility that we consider in the Appendix is that people could disproportionally move to regions that receive more funding. If the rich are more likely to move to these regions than the poor, incomers could be among the recipients of the gains for upper-income groups. Table A.5 in Appendix C.3, however, shows that the place-based policy does not lead to in-migration to regions that receive more funding. The gains from the policy thus primarily go to current inhabitants.

Rents. As a third alternative mechanism, we also look at the effects of EU funds on housing costs in Appendix C.4. In theory, place-based financial support could lead to higher 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 these may live in other regions. As all surveys that we consider also include data on *housing costs*, we can test the hypothesis that place-based funding increases local rents. As results in Figure A.9 show, we do not find significant effects on housing costs for any decile group.

6 Additional Evidence from a DiD Design

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 on a combination of spatial and temporal variation. To test whether our findings hold in a different empirical set-up, we isolate the temporal dimension with a DiD design and study an episode in which two groups of regions lost access to different amounts of place-based funding.

This analysis examines 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, because in 2006 there were two reasons for losing eligibility. First, multiple funded regions 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 EU, reducing the EU's average GDP per capita. 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, such that 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. To reduce the disadvantage that this meant for these regions, the EU granted these regions so-called "phasing-out" support; a limited amount of transitory place-based funding for the 2007-2013 period that was substantially smaller than what they would have received as fully eligible regions.

To estimate the consequences of losing access to the place-based policy, we study the two groups of regions that lost eligibility in 2006/7 and compare them to the regions that remained eligible with the following two-way-fixed-effects (TWFE)[30] model:

[30] As there is no staggered treatment, the problems of TWFE regressions that the recent DiD literature has identified do not apply here (de Chaisemartin and D'Haultfoeuille 2022).

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

where D indicates, depending on the specification, either the "phasing-out regions," the regular dropout regions, or all dropout regions. The coefficient of interest β indicates 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 the 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 identify the timing of the effects, we allow the estimates to vary by year and estimate the following event-study specification:

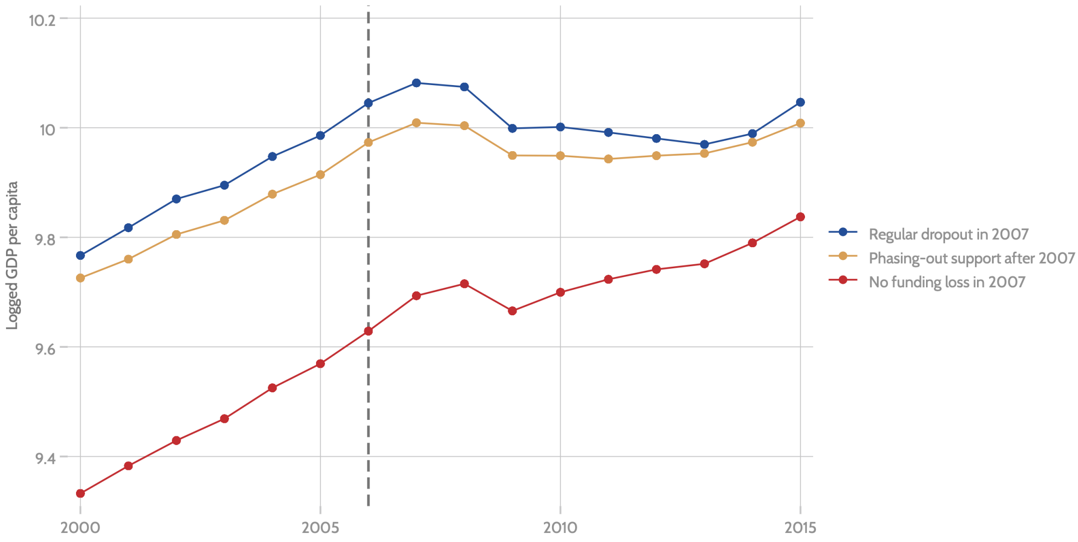
$$y_{rt} = \alpha_r + \tau_t + \sum_{t=2000}^{2013} \beta_t(\mathrm{D}_r \times \tau_t) + \varepsilon_{rt} \tag{7}$$

In this model, the dropout region indicator D is interacted with year fixed effects (τ). As official decisions on eligibility in the 2007-2013 funding period were made in May 2006 (Pritzkow 2006), we consider 2006 as the first treated year in order to capture any difference between the groups after the official announcement of the changes in policy eligibility.

6.2 Parallel Trends: Descriptive Evidence

Before turning to the regression results, we descriptively examine the trends of economic growth in regions that lost eligibility in 2006/7 and in regions that remained eligible. Figure 14 plots averages of GDP per capita before and after the treatment in 2006 across the three groups of regions (regular dropout, phasing-out support, no funding loss). Differences before the treatment are as expected: Regions that dropout regularly are substantially richer than regions that remain eligible and somewhat richer than regions that receive phasing-out support after 2006. Crucially, all three groups are on a parallel growth path before 2006, enhancing the plausibility of the DiD assumption that trends would have remained parallel in the counterfactual absence of funding loss. After the treatment, however, trends stop being parallel. Regions that remain eligible grow faster than regions that stop being eligible. Phasing-out regions with limited transitional support grow faster than ineligible regions but more slowly than regions with full access. While these descriptive trends give a first indication of the effect of losing access to EU funds and enhance the parallel-trends assumption, we turn to a regression-based approach below.

Figure 14: Trends in GDP per capita before and after 2007



Notes: Unweighted averages of logged GDP per capita across the three groups of regions. The dashed line indicates the end of the 2000-2006 funding period, in which all three groups were fully eligible.

6.3 Results: DiD

6.3.1 Two-period DiD

Table 8 reports the results from estimating the DiD model specified in equation 6. Panel A examines the effect of losing eligibility on economic growth. We find substantially negative effects on GDP per capita growth across the three specifications. The average effect of losing eligibility for all dropout regions is estimated at -1.9 percentage points. Differentiating between the regions with and without *phasing-out support* shows that the effect is smaller in regions that benefited from the transitory place-based support (-1.0 vs. -3.3 percentage points). For policymakers, this points to the potential of transitory schemes to cushion adverse effects of withdrawing place-based funds. Panel B turns to the distributional effects of losing access to the place-based policy and shows that there is a negative effect on the Gini index of 0.9 points. Again, the estimate is smaller for the regions that received *phasing-out support* than for those that did not (-0.7 vs. -1.1), supporting the view that the amount of lost funds matters.

These results support the main results of the RD design by adding evidence on the temporal dimension from when place-based funding ends: Regions that lose access to the place-based funds see a decrease in economic growth and in inequality relative to the regions that remain eligible. These effects are larger for regions that lose more place-based funding.

Table 8: DiD estimates of the 2006/7 funding loss

Panel A: GDP per capita growth			
	(1)	(2)	(3)
All dropout regions × Post	-1.93		
	(0.62)		
Phasing-out regions × Post		-1.03	
		(0.81)	
Regular-dropout regions × Post			-2.93
			(0.69)
Observations	1242	1090	1074
Panel B: Gini coefficient			
	(4)	(5)	(6)
All dropout regions × Post	-0.91		
	(0.51)		
Phasing-out regions × Post		-0.73	
		(0.58)	
Regular-dropout regions × Post			-1.06
			(0.74)
Observations	902	799	799
Region FE	✓	✓	✓
Year FE	✓	✓	✓
Control regions	still eligible	still eligible	still eligible

Notes: TWFE 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 regions that remained fully eligible in the 2007-2013 funding period. Standard errors clustered by NUTS 2-regions are reported in parentheses.

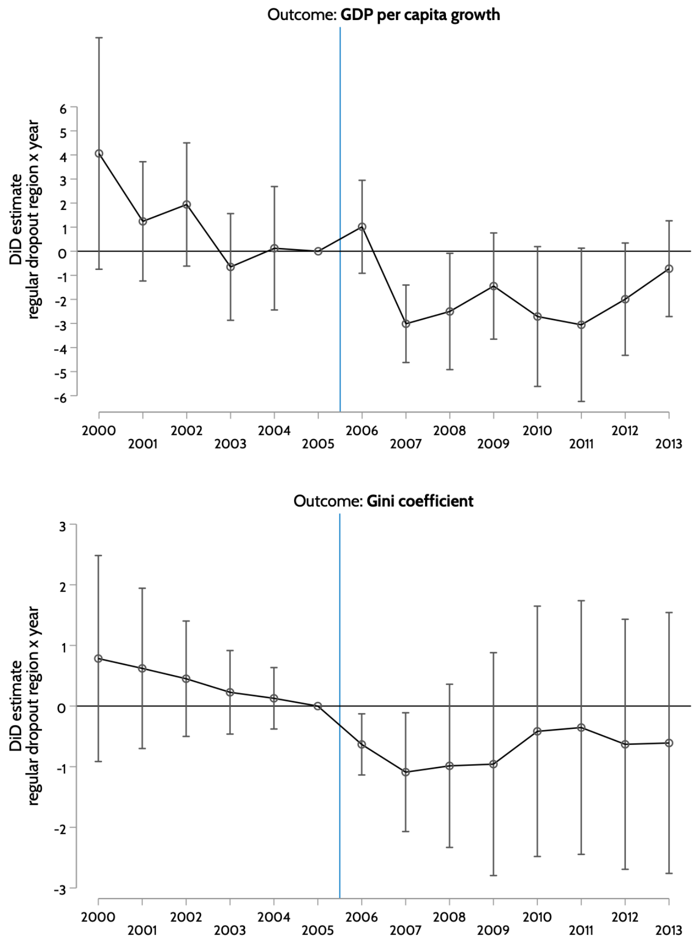
6.3.2 Event Study

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 15 plots the results of estimating equation 7 for regular dropout regions without transitory support.[31]

Panel A studies annual growth rates of GDP per capita to estimate how average incomes react to the loss of place-based funding. There are no statistically significant differences between treated regions and control regions before the former lose eligibility. The first significantly negative coefficient is observable in 2007, the year after the decision was made. For the subsequent years, the annual growth rates are substantially lower in regions that lost access to place-based funds. Panel B turns to the Gini coefficient. The first significantly negative coefficient is observable in 2006, the year in which the decision on eligibility were made. For the entire post-2006 period, estimated differences between *phasing-out* and control regions are substantially below all pre-2006 differences.

[31] Analogous results for the regions with transitory support and for all dropout regions are reported in Appendix F.

Figure 15: Event Study



Notes: Event-study plots (see equation 7). The figures plot the estimates of β_t along with 95% confidence intervals. Outcome variables are GDP per capita growth (Panel A) and the Gini coefficient (Panel B).

The quite sudden effect of the policy change could reflect changing investment decisions taken as soon as the loss of place-based funding could be foreseen, leading, for instance, to a reduction in job creation for highly skilled workers. Results in Appendix F show that these effects are, again, smaller for regions that received transitory support.

Overall, these results further support the main conclusions drawn from the RD analysis: The place-based policy increases mean incomes but also income inequality within regions. As soon as access to the funds was lost, inequality levels in supported regions declined.

7 Conclusions

Inequality across regions has been identified as a major challenge in most advanced economies. To fight inequalities and foster economic convergence across regions, policy-makers direct large sums of money to poor regions. But income inequality within these regions is substantial. 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." Until now, it had remained unclear whether place-based policies generate income gains for the rich or the poor in the regions that they target.

We find that the world's largest place-based policy benefits rich people in supported regions much more than it benefits their 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 groups 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 the effects are similar in other contexts. More generally, both the theoretical and the empirical 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. However, their potential to address overall inequality and provide 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 questionable whether they deliver on this promise. Quite the contrary, their distributional effects might even exacerbate political discontent and reinforce feelings of being left behind. In the context of growing political polarization across regions, research on this question seems timely.

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For Online Publication

Online Appendix

to

"Place-Based Policies and Inequality Within Regions"

A Online Appendix

Contents

A Data on Regional Inequality in Europe

A.1 Construction of the Data Set

We construct a large data set on income inequality across and within regions for a panel of subnational regions in Europe. To do so, we collected household-level and individual-level data from a total of 260 national household surveys. Table A.1 gives an overview of the data sources we combined.

LIS data. We use a total of 86 national surveys that are compiled by the Luxembourg Income Study (LIS). The advantage of LIS is that the income data are already harmonized across countries. The household-level data of these surveys, however, cannot be downloaded but can only be accessed via a remote-execution system (named LISSY) that allows researchers to access the data from a remote location. We thus process these data via LISSY to produce the variables at the region-year level that we require for our analysis. This data processing includes a re-coding of the geographic identifiers as LIS surveys do not use the NUTS-2 geocode standard. For each country and year for which it is possible we map LIS's geographic identifiers to NUTS-2 regions while accounting for administrative reforms in the observation period. 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.

SILC data. For countries, where the geographic identifiers included in LIS are not sufficiently granular, we turn to data from EU-SILC. We use data from 135 national surveys from their "confidential data for scientific purposes" that require an application and approval by the European Commission. Like LIS data, income data contained in SILC surveys is already harmonized but the earliest available year is 2003, which is why we prioritize LIS data. For most countries, the household-level data includes information on the NUTS-2 region in which the household is located. For Germany and the United Kingdom, however, only the larger NUTS-1 regions are reported in SILC and we turn to additional national surveys for these two countries.

SOEP data. For regions in Germany we use the restricted-use files of the Socio-Economic Panel (SOEP), which include granular geographical identifiers for each household. We map those to NUTS-2 regions and account for administrative reforms in Germany in the observation period. The data cover the entire observation period. SOEP income concepts are very similar to the income concepts used in SILC.

BHPS and Understanding Society data. For regions in the United Kingdom we acquired the restricted-use files of the British Household Panel Study (BHPS) for the 1991-2008 period and Understanding Society for the 2009-2017 period. These surveys report so-called local authority districts for each respondent and we map those to NUTS-2 regions with based on official maps. The income types reported in BHPS and Understanding Society are somewhat different than those reported in other data sets but by aggregating and dis-aggregating we are able to reproduce the same differentiation of income types that is applied in LIS. Moreover, some incomes types are reported at a monthly level and we transform them into annual incomes by multiplying them by 12. Note that we only use Understanding Society data when differentiating between income types (because of changing definitions) and for the DiD analysis (to avoid breaks in the time series for the UK).

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Data processing. The data from various sources and various countriers are reported in various currencies and price levels and we thus adjust them to 2011 international dollars at purchasing power parity (PPP) based on data from the World Bank. The various data sources also report different types of income. All sources report disposable income, which we use in the baseline, and apply the same definition. For other types of incomes (labor income, capital income, transfers) we apply the LIS definitions to all other sources. For most analyses we use household-level data and adjust for differences in household sizes by applying the square-root scale, which is recommended by LIS. For the analyses at the individual-level we use the alternative, individual-level data sets that all sources provide in addition to the household-level data sets.

Table A.1: Overview of data sources for regional income and inequality measures

source	countries	time periods	geography
British Household Panel Survey (BHPS)	England, Northern Ireland & Scotland	1989-2008	UK local authority district
Understanding Society	England, Northern Ireland & Scotland	2009-2017	UK local authority district
German Socio-Economic Panel (SOEP)	Germany	1989-2017	NUTS-2 region
Luxembourg Income Study	Austria, Estonia, Greece, Hungary, Ireland, Italy, Lithuania, Poland, Sweden, Slovakia	1989-2017	country-specific region
EU Statistics on Income and Living Conditions (EU-SILC)	Croatia, Cyprus, Czechia, Finland, France, Luxembourg, Latvia, Malta, Spain	2003-2017	NUTS-2 region

A.2 Validation of Data Quality

We conduct a number of analyses to check the quality of the household-level data when aggregated to the regional level. First, we compare the regional mean of household incomes to regional GDP per capita from national accounts. As these are similar but not identical constructs we should see strong but imperfect correlations between the two measures. Furthermore, we should be able to explain differences between the two measures for regions where the values differ strongly.

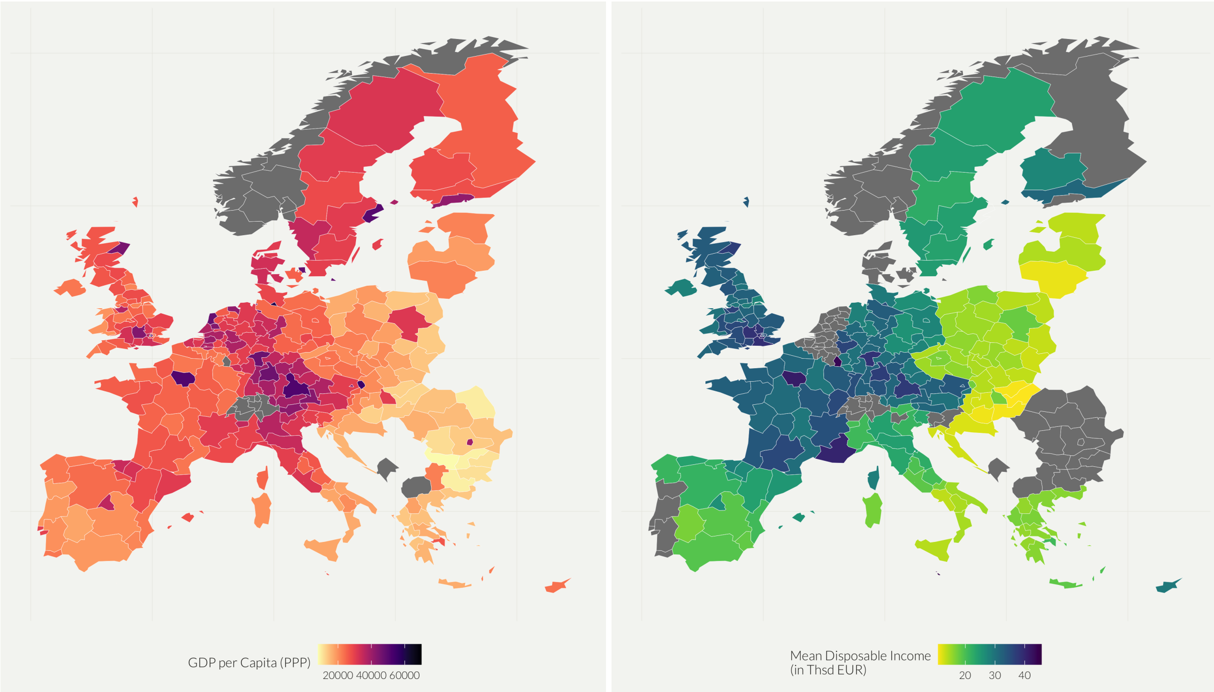
Geographic patterns. Figure A.1 compares regional levels of GDP per capita from national accounts to the regional mean of disposable household income from the national surveys. A strong correlation between the two measures is immediately visible. According to both measures, the largest values are recorded for the capitals of France and the UK as well as for regions in Southern Germany. Both measures also show similar differences between Southern and Northern Italy as well as between Southern and Northern Spain. Differences between Eastern and Western Europe are also clearly visible.

An instructive example for a region where the two variables differ is the region of Provence-Cote d'Azur in Southern France. The region is famous for the large number of rich people that live on the coast of Southern France in cities like Nice, Cannes and St. Tropez. This is reflected in high mean incomes (see Panel **(b)**). Their incomes, however, often results from investments in or work for businesses that are located in other parts of France, often Paris. This is why the regional GDP per capita in this region is not substantially higher than in the surrounding regions (see Panel **(a)**).

Correlations. 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. Figure A.3 shows a scatter plot of these two measures. As is visible, the correlation is positive and strong. The overall correlation coefficient of the two measures is $\rho = 0.77$.

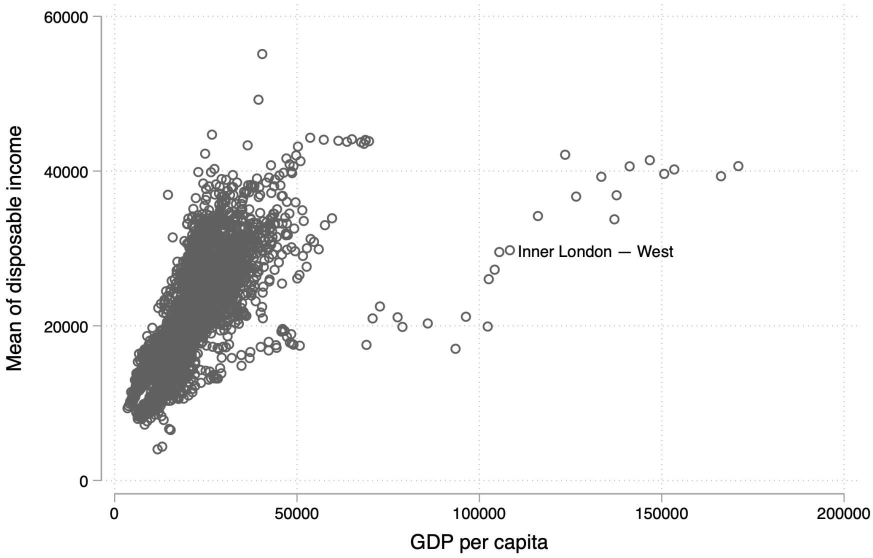
Figure A.1: Comparing regional data from national accounts to household data

(a) Regional GDP per capita **(b)** Regional mean of household incomes



Notes: Panel **(a)** plots regional GDP per capita for the latest available year from national accounts. Panel **(b)** plots regional means of disposable household income, latest available year.

Figure A.3: Regional mean income and regional GDP per capita

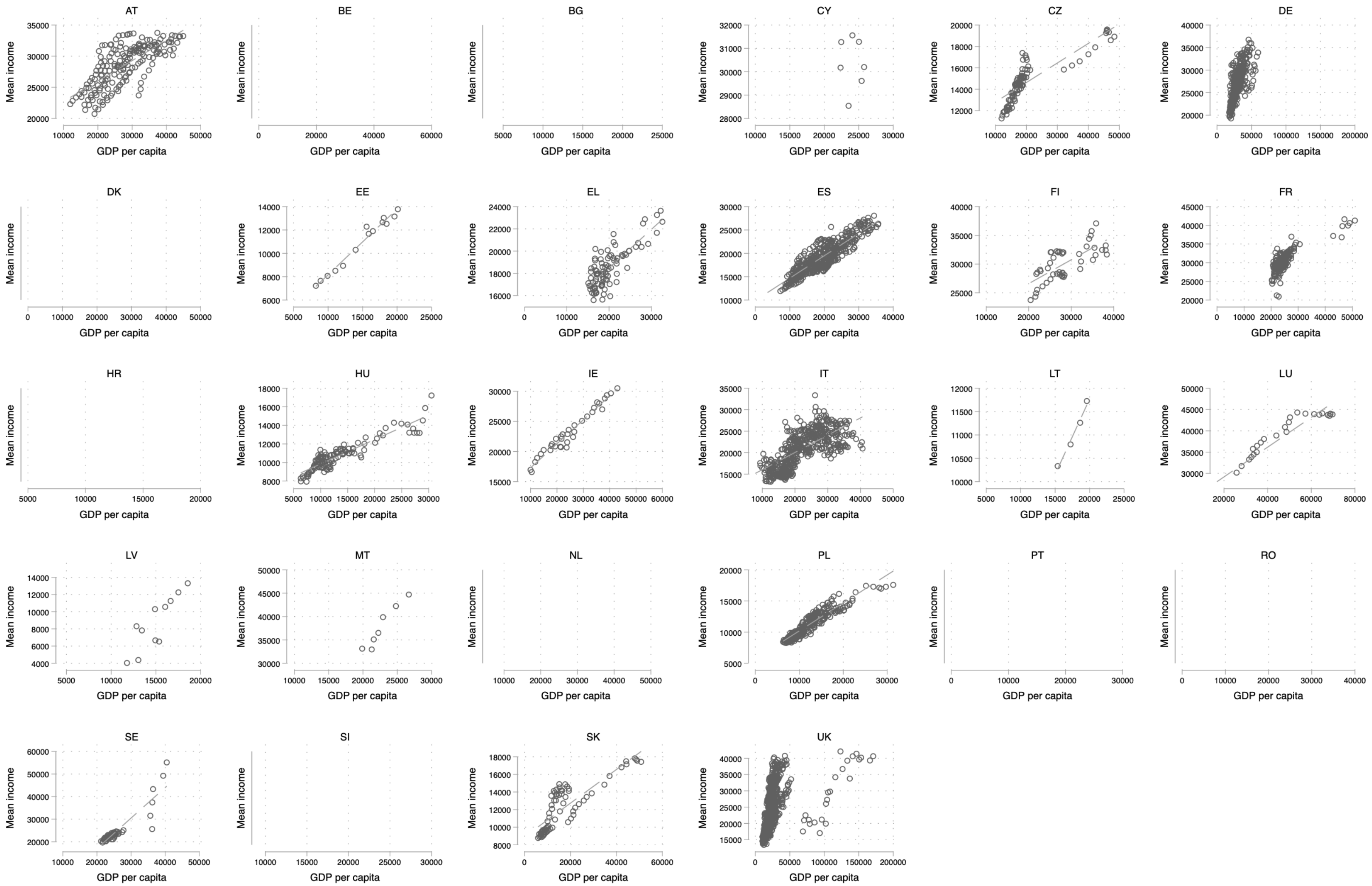


Notes: The figure plots GDP per capita on the x-axis against the regional mean of disposable household income. The outlying observations on the right are all from *Inner London, West*

In this figure, 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 "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 A.4 repeats the same exercise for each country separately. The figures show consistently positive and strong correlations in each country. The country-wise correlation coefficients range between 0.62 and 0.99.

Figure A.4: Regional mean income and regional GDP: correlations by country

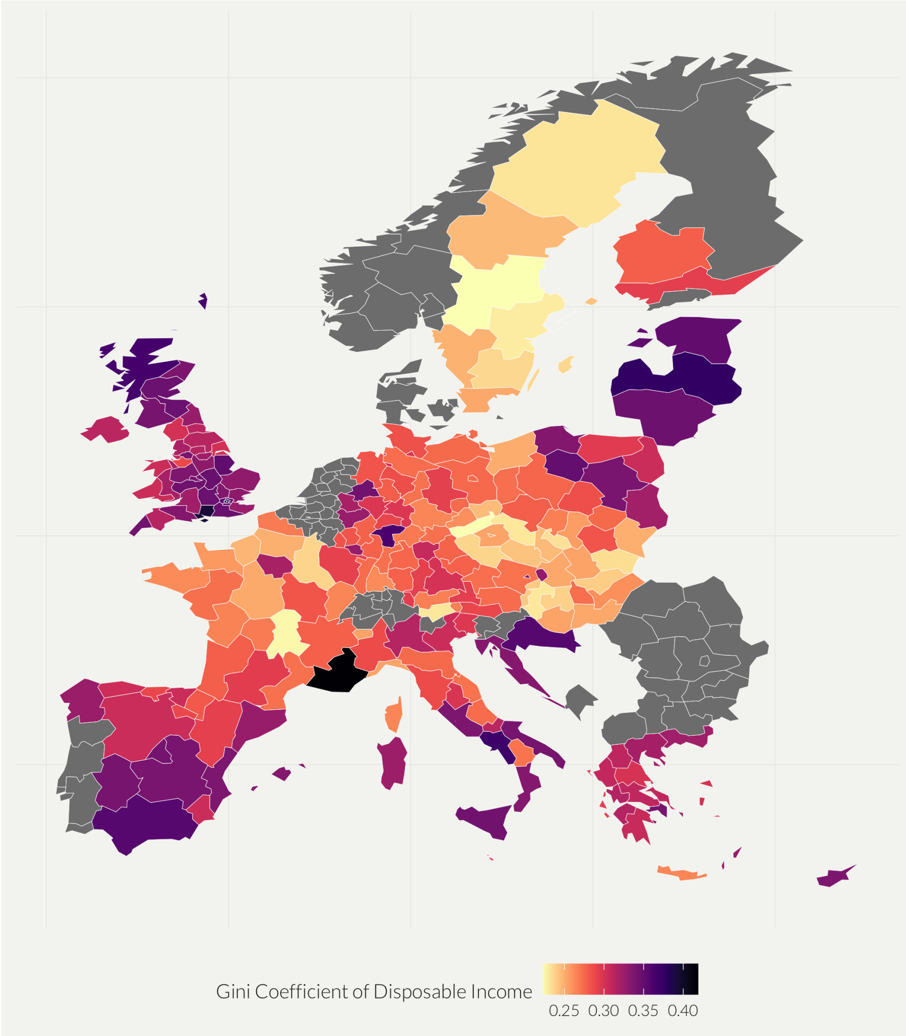


Notes: The figure plots regional GDP per capita on the x-axis against the regional mean of disposable household income for each country in the sample.

A.3 Additional Stylized Facts on Inequality in Europe

Geographic variation. In Figure 3, we plot region-specific Gini indices 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, however, substantial regional variation. We note the following patterns: First, 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. Second, there are important differences within countries. For instance, in both Spain and Italy, southern regions are more unequal than northern regions. Northern Poland is more unequal than Southern Poland. Third, the most unequal region in the EU is the French region of Provence-Alpes-Cote d'Azur with a regional Gini of 0.40. A potential explanation for this could lie in the income differences between a rich coast (St. Tropez, Cannes, Nice) and a poorer, rural hinterland. The most equal region is the North West of the Czech Republic (Severozapad) with a regional Gini of 0.22.

Figure A.5: Regional Gini indices



Notes: The map shows regional Gini indices of disposable household income based on household data for the latest available year.

Income levels and income distributions. Is the regional mean of incomes correlated with the inequality of these incomes? In Figure A.6, we plot regional Gini indices against the regional mean of disposable household incomes. As is visible, there is substantial variation in both regional mean incomes and intra-regional inequality across European regions. The cross-regional Gini coefficient of regional mean income is at 0.152 and thus considerably smaller than the average intra-regional Gini coefficient of 0.299. This reflects the finding discussed in the main text that inequality within regions is an important component of overall inequality in Europe. Overall, there seems to be a weak positive association between regional mean incomes and inequality. Richer regions tend to be slightly more unequal on average, but among both rich and poor regions, there are both relatively unequal and relatively equal regions.

Another conclusion that can be drawn from this is that for inequality within European regions, there is no evidence for a turning point above which inequality declines (as discussed in Kuznets (1955)).

Figure A.6: 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.

A.4 Income concepts

Throughout the paper we use a variety of income concepts to process the data contained in household surveys. We apply the LIS definitions of income concepts to all household surveys that we use.[32]

Disposable Income. In the baseline analysis, we use disposable household income, defined as *total gross household income* minus *income taxes* and *social security contributions*. *Total gross household income* includes labor income, capital income, pensions, public social benefits and private transfers. By dividing each household's disposable income by the square root of household members, we calculate *equivalized* disposable household income. For a number of analyses, we assign each household to its decile according to this measure to derive decile-specific measures of income levels and income growth.

Labor Income. This income concept includes all household income derived from labor including wage income and income from self-employment. For most households in the sample, it is the main source of income. Note that this is *gross* labor income. For the decile-specific analyses, we calculate the growth rate of equivalized labor household income separately for each decile by equivalized disposable household income (see above).

Capital Income. This income concept includes all household income derived from capital including interests, dividens, and rental income. For the decile-specific analyses, we calculate the growth rate of equivalized capital household income separately for each decile by equivalized disposable household income (see above).

Transfer Income. This income concept includes all household income derived from transfers including public social benefits, pensions, and private transfers. Together with labor income and capital income, transfer income is the third and last component of total income. For the decile-specific analyses, we calculate the growth rate of equival-

[32] https://www.lisdatacenter.org/wp-content/uploads/files/data-lis-variables.pdf

ized transfer household income separately for each decile by equivalized disposable household income (see above).

Total Gross Household Income. The sum of *labor income*, *capital income*, and *transfer income*.

Housing Costs. This variable captures all household expenses for housing and includes rent payments, property taxes and mortgage installments.

Income by Degree of Urbanisation. For the analysis in section C.2, we differentiate between households in rural and urban areas and calculate growth rates of equivalized disposable household income for the two types of areas in each region separately.

Income by Level of Education. For the analysis in section 5.3, we switch from household-level data to individual-level data. We focus on individual-level labor income and restrict the sample to the working age population. We then harmonize individual-level measures of education levels across surveys. While different surveys use different education measures, we are able to map all of them onto a trichotomous measure. For the analyses, we then calculate growth rates of labor income for each of the three education levels in each NUTS-2 region and each year.

B Other Data

B.1 Additional Outcome Variables

In addition to the data on household incomes described above, we use the following outcome variables from other sources:

GDP per capita. Data on regional GDP per capita growth is taken from Eurostat. For the regressions, we use the annual growth rates of PPP-adjusted GDP per capita at the NUTS-2 regional level.

Investment. Data on investments are the gross fixed capital formation series by Eurostat. For the regressions, we use the annual growth rates of this variable at the NUTS-2 regional level. We use both total investment as well as sector-specific investment. The disaggregation of sectors follows Eurostat.

Employment. Data on employment is taken from Eurostat. We compute regional employment rates by dividing the number of employed persons by the region's population size. For the regressions, we use annual changes in these employment rates as outcome variables. We use both total employment as well as sector-specific employment. The disaggregation of sectors follows Eurostat.

Unemployment. Data on unemployment rates is taken from Eurostat. Analogous to employment, we use annual changes in unemployment rates as outcome variables.

Migration. As measures of migration into and out of regions we use two variables from Eurostat. One is the annual regional population growth at the NUTS2 level. The other is the crude rate of net migration into regions.

B.2 Data on the RD Forcing Variable

Our RD design requires exact data on the forcing variable, i.e., the NUTS2 regions' GDP per capita in relation to the EU average. Existing research on the EU's place-based policies has typically used regional data from national accounts reported by Cambridge Econometrics or Eurostat to calculate this variable. There are two problems with using such data to calculate the forcing variable for RD designs: a) regional GDP figures are repeatedly revised and today's data thus differ from the data that were available at the time the allocation decisions were made; b) the years that were used as reference years for the allocation decisions differed across programming periods and regions. When we applied this approach of using national-accounts data in early stages of our work in this project, we found highly imperfect compliance with the allocation rule, which we considered implausible.

We thus approached staff of the European Commission (EC) and asked for the original data that were used by the EC at the time the allocation decisions were made. After multiple unsuccessful attempts, we received these data from a very cooperative staff member. The data on the official EU calculation of the forcing variable were shared in the form of separate files for the programming periods 2000-2006, 2007-2013, 2014-2020. For the programming periods 1989-1993 and 1994-1999 we did not receive the calculated forcing variables but the old vintages of the Eurostat data that were used for these calculations. Through correspondence with EC staff, we were able to reconstruct the original calculations that were made at the time.

With this approach, we find almost perfect compliance with the official allocation rule. There are 15 exceptions and we study those in detail on a case-by-case basis in Table A.2. Through an extensive web research based on official EU documents, we find an explanation for the non-compliance for each of these 15 cases. This enhances our confidence that the data we use are the original data that were used for the official allocation decisions.

Table A.2: 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.

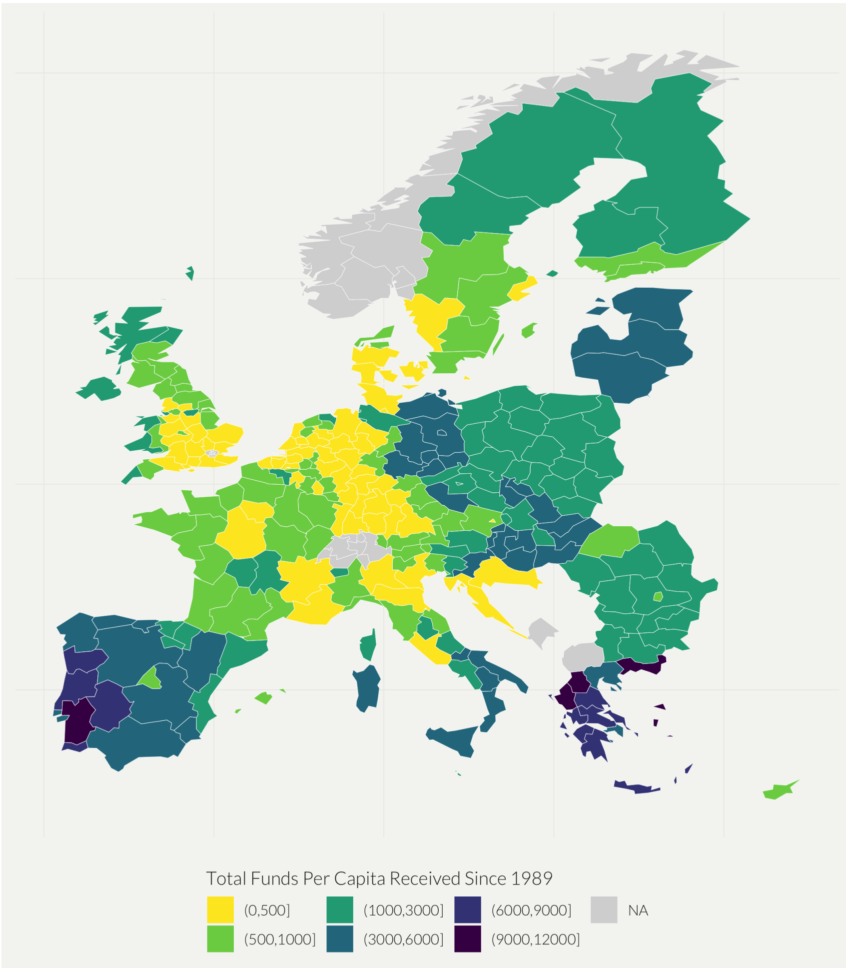
Note: This table lists all regions that received eligibility status even though their GDP per capita exceeded the threshold value. See Figure 7.

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

B.3 Data on Treatment Variables

Disbursements. Figure A.7 gives an overview of the disbursements of funds across European regions. The map plots total per capita spending in the observation period. Accordingly, the largest values are recorded for relatively poor regions of countries that were EU members since the launch of the policy in 1989 (e.g., Southern Portugal, Southern Spain, Greece). In many of these regions more than EUR 10.000 per capita were spent in the observation period.

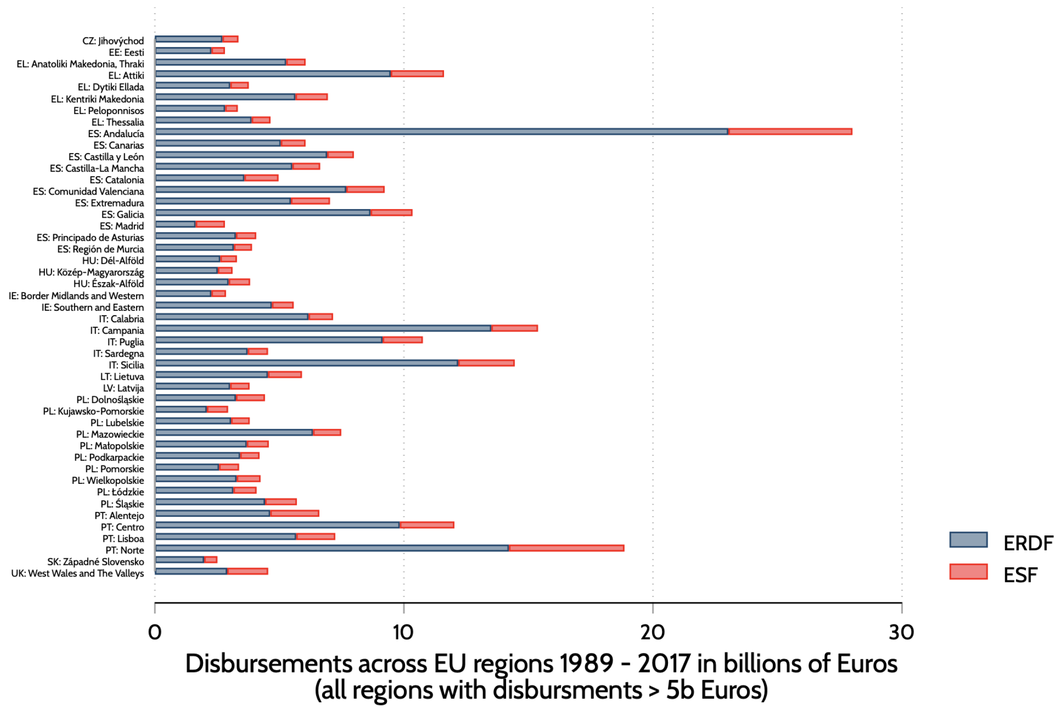
Figure A.7: Disbursements of EU Funds Across Regions



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

ERDF and ESF. Figure A.8 plots total disbursements for all regions that received more than EUR 5 billion in the observation period. It also differentiates between the two main components of the policy, the ERDF and the ESF. While it would be interesting to study the two components separately, their allocation follows the same allocation rule and there is thus no quasi-exogenous source of variation that we can leverage to study potential differences between them. However, as the graph suggests that the relative share of the two funds is quite similar across regions, we suspect that the limited variation in relative shares of the components across regions will not result in substantial differences.

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



C Additional Results

C.1 Unemployment

Section 5 studied the effect of the place-based policy on employment rates across various sectors. Table A.3 complements this analysis by studying the policy's effect on various measures of unemployment. In addition to studying the overall unemployment rate in the first column, models 2 and 3 isolate long-term unemployment and youth unemployment, respectively. Eligibility for the policy reduces both overall unemployment and long-term unemployment by about 0.4 to 0.5 percentage points. Youth unemployment is reduced by about one percentage point. It should be noted, however, that the youth unemployment rate is on average more than twice as large as the overall unemployment rate.

Table A.3: 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 bias-corrected RD estimates with robust nonparametric standard errors, which are clustered at the NUTS2-level and reported in parentheses. All regressions use a *triangular kernel* and an RD bandwidth of *40*. The forcing variable is *GDP per capita as a share of the EU average*.

C.2 Rural and Urban Places

The smallest geographical unit that can be studied in the main analysis in the NUTS2-region, as more granular geographical identifiers are not available for the data that are needed for this analysis. To study the geographical distribution of the growth effects within NUTS2 regions, we turn to an alternative approach. Many NUTS2-regions comprise both urban and rural areas and the household-level survey data include information on the degree of urbanization in the household's surrounding. We use this information to distinguish between growth effects in rural and urban areas of supported NUTS2 regions. Table A.4 reports the results. They suggest that effects in rural and urban areas are similar. While the point estimate for urban regions is somewhat larger, the two coefficients are not statistically different from each other. These findings on the spatial distribution of funds within regions do not provide an explanation for the policy's distributional effects.

Table A.4: Rural and Urban Places

	DV: Income growth	
	Rural	Urban
Eligibility	0.247	0.349
	(0.663)	(0.414)
Country FE and Year FE	✓	✓
Observations	395/422	401/451
Mean income	19259	21024

Notes: The table reports local linear bias-corrected RD estimates with robust nonparametric standard errors, which are clustered at the NUTS2-level and reported in parentheses. All regressions use a *triangular kernel* and an RD bandwidth of *40*. The forcing variable is *GDP per capita as a share of the EU average*.

C.3 Migration

In Table A.5, we test whether the place-based policy leads to migration into the supported regions. One concern on our results could be that the income gains that we record do not reach the native population of these regions but are obtained by people that move to these regions because of the place-based support. We thus collect region-year-level panel data on a) population growth, and b) the crude rate of net migration into regions. Irrespective of the measure that is used and irrespective of whether this is estimated as a sharp RD or a fuzzy RD, there is no statistically significant evidence for the hypothesis that the place-based policy leads to in-migration to regions that receive more funding. This suggests that the income gains go primarily to current inhabitants.

Table A.5: Migration into Supported Regions

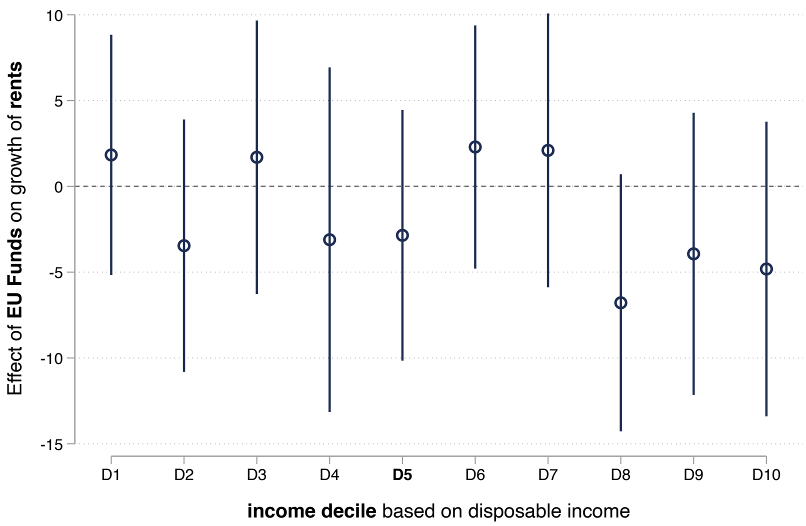
	DV: Population Growth		**DV: Net Migration Rate**	
	Sharp RD	Fuzzy RD	Sharp RD	Fuzzy RD
RD estimate	0.029	-0.039	0.210	-0.212
	(0.035)	(0.043)	(0.235)	(0.237)
Country FE and Year FE	✓	✓	✓	✓
Observations	1342/3335	1341/3299	968/1789	968/1789

Notes: The dependent variable is growth of population per region and year in percent. The table reports local linear bias-corrected RD estimates with robust nonparametric standard errors, which are clustered at the NUTS2-level and reported in parentheses. All regressions use a *triangular kernel* and an RD bandwidth of *40*. The forcing variable is *GDP per capita as a share of the EU average*.

C.4 Rents

As discussed in the main text, place-based financial support could lead to higher rents and housing costs 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 these landlords may live in other regions. All household surveys that we consider include data on *housing costs*. We use these data to compute the region-year-decile specific growth rate of housing costs. We then use this variable as an outcome for our baseline RD estimations. As the results in Figure A.9 show, there is no statistically significant effects on housing costs for any income decile. The average effect on the growth rate of housing across all intra-regonal deciles is also not statistically different from zero. There is thus no empirical support for the concern that local income gains are absorbed by landlords.

Figure A.9: Effect on housing costs by decile



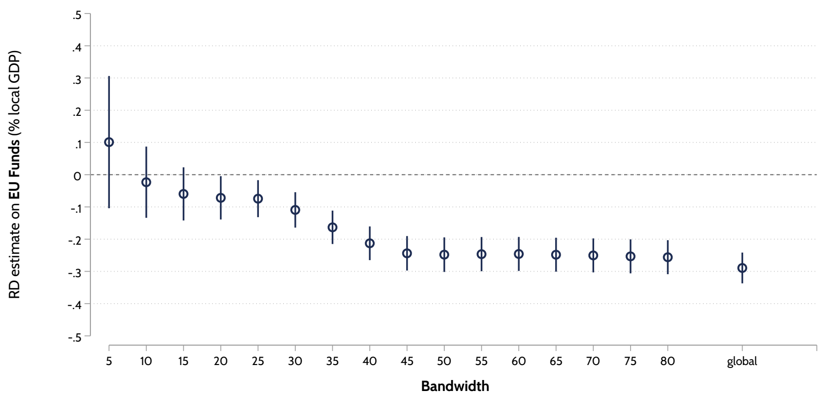
Notes: Coefficients of **EU Funds** and 95% confidence intervals. The dependent variable is the growth of housing costs for the ten decile groups by disposable income. Otherwise the regressions are identical to the baseline regressions plotted in figure 10.

D Robustness: RD Design

D.1 Varying the RD Bandwidth

As mentioned in the main text, we estimate the RD regressions for a wide variety of bandwidths to show that the results do not depend on the bandwidth selection. In this section, we present these results. Figure A.10 again shows the results for the first-stage effect on actual disbursements, which were plotted in Figure 9 in the main text. As discussed above, the local linear regression estimate statistically significant (95% level) discontinuities in received place-based funding for all bandwidths equal to or larger than 20. An intuitive explanation is that with smaller bandwidths, the sample is underpowered and the number of non-compliant, exceptional cases is high relative to the small sample used for these regressions. When allowing the sample to become larger, regular observations receive more weight and the drop in funding is statistically significant for all bandwidths except the extremely small ones. This includes a "global" bandwidth that uses the entire sample, as in previous literature (Becker et al. 2010).

Figure A.10: Varying the Bandwidth: Effects on **EU Funds**

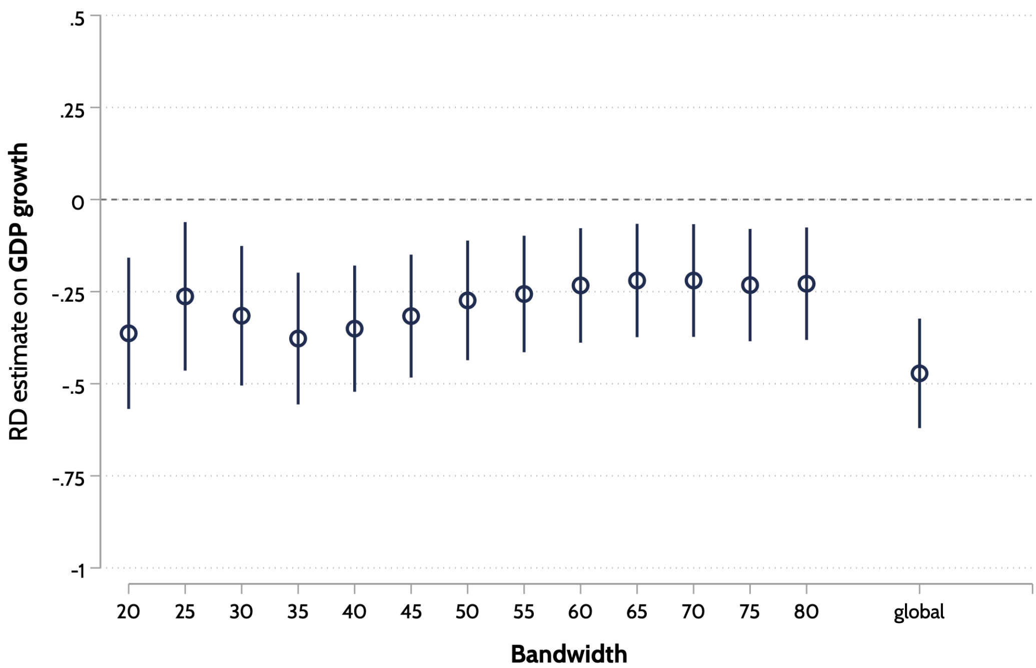


Notes: Coefficient plot of local linear bias-corrected sharp RD estimates with robust nonparametric standard errors, clustered at the NUTS2-level, based on equation 2. The regressions use a triangular kernel and varying bandwidths. Outcome variable *EU funds (% GDP)*. 95% confidence intervals.

As a significant first-stage effect on funding disbursements is necessary to observe any potential economic effect, we study the robustness of the second-stage effects to estimation with all bandwidths equal to or larger than 20. The largest bandwidth we study is 80 as larger bandwidths lead to samples that are close to the global sample, which we also plot separately. Our baseline bandwidth of $h^{\star} = 40$ allows us to show results for all bandwidths between $\frac{h^{\star}}{2} = 20$ and $2h^{\star} = 80$.

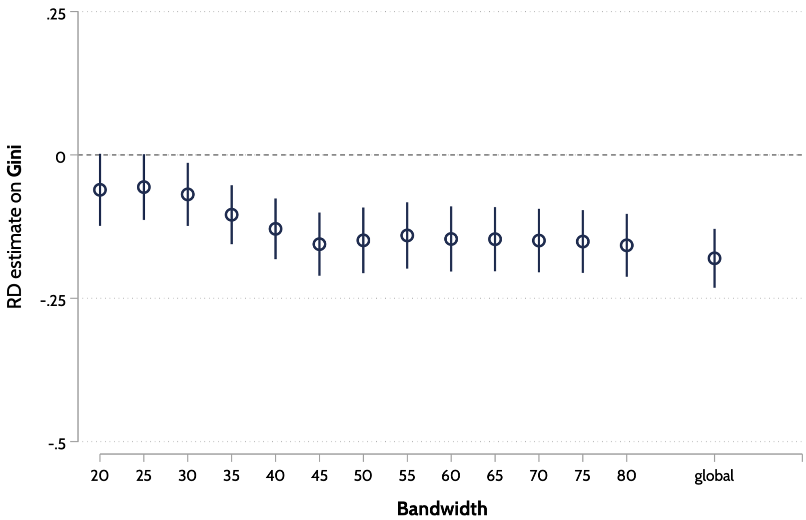
Figure A.11 plots the results for aggregate growth. Figure A.12 plots the results for inequality as measured by the Gini coefficient. Both coefficient plots reveal that the results do not depend on the bandwidth that is selected. All bandwidths between 20 and 80 yield coefficients that are statistically significant at the 95% level. Moreover, the baseline bandwidth of 40 leads to point estimates that are representative for the set of point estimates that are estimated when other bandwidths are used.

Figure A.11: Varying the Bandwidth: Effects on **GDP Growth**



Notes: Coefficient plot of local linear bias-corrected fuzzy RD estimates with robust nonparametric standard errors, clustered at the NUTS2-level, based on equation 2. The regressions use a triangular kernel and varying bandwidths. Outcome variable: *GDP per capita growth*. 95% confidence intervals.

Figure A.12: Varying the Bandwidth: Effects on **Inequality of Household Incomes**

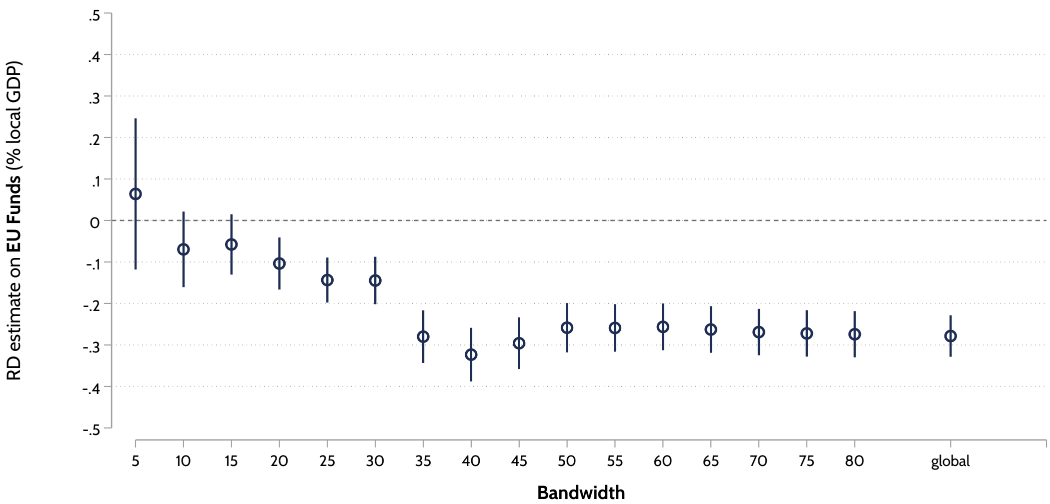


Notes: Coefficient plot of local linear bias-corrected fuzzy RD estimates with robust nonparametric standard errors, clustered at the NUTS2-level, based on equation 2. The regressions use a triangular kernel and varying bandwidths. Outcome variable: *Gini coefficient*. 95% confidence intervals.

D.2 Uniform Kernels

In the main body we chose a triangular kernel to estimate our RD models. This means that observations closer to the cut-off are given more weight in the regressions. Given that the key idea of an RD design is to primarily leverage variation around the threshold, a triangular kernel is a common approach in the literature. Below we report the robustness of these findings by changing our approach to a uniform kernel. This means that we refrain from giving more weight to observations closer to the cut-off. To be transparent, we re-estimate the models with a uniform kernel for all bandwidths. Figures A.10, A.11 and A.12 plot the results in the form of coefficient plots.

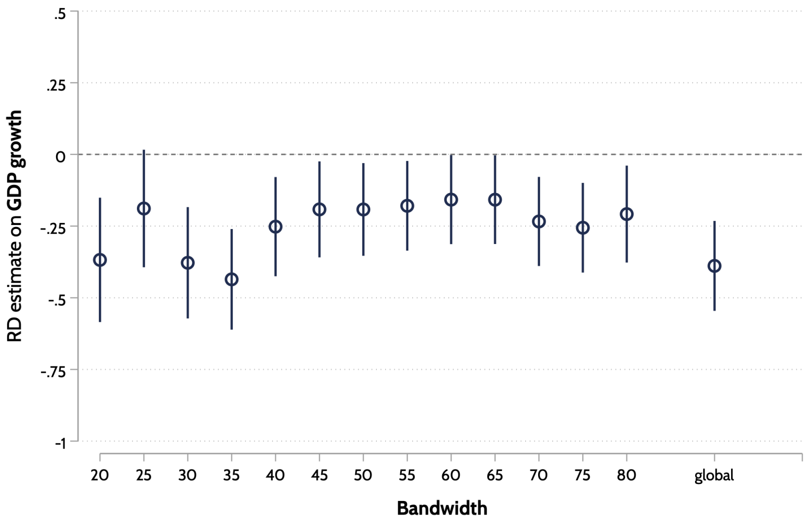
Figure A.13: Uniform Kernel: Effects on **EU Funds**



Notes: Coefficient plot of local linear bias-corrected sharp RD estimates with robust nonparametric standard errors, clustered at the NUTS2-level, based on equation 2. The regressions use a uniform kernel and varying bandwidths. Outcome variable *EU funds (% GDP)*. 95% confidence intervals.

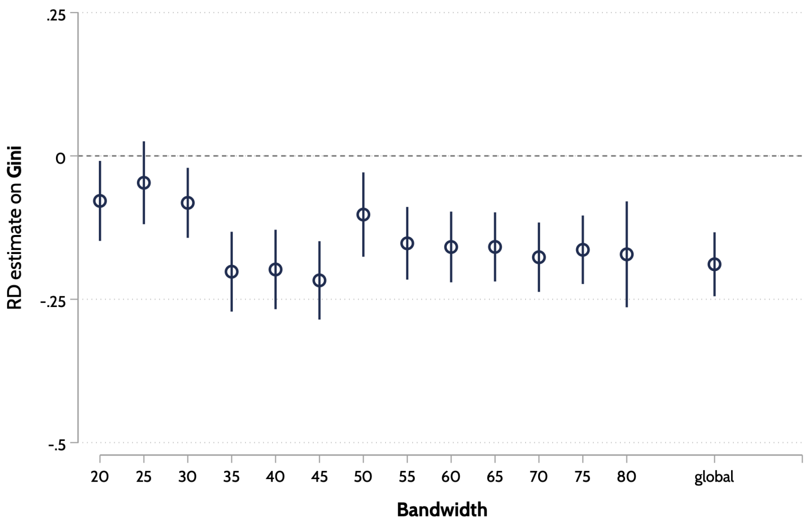
The figures show that the results are robust to changing the triangular kernel to a uniform kernel. The changes in the point estimates along with the confidence intervals reflect the patterns discussed in relation to the selection of the bandwidth (D.1).

Figure A.14: Uniform Kernel: Effects on **GDP Growth**



Notes: Coefficient plot of local linear bias-corrected fuzzy RD estimates with robust nonparametric standard errors, clustered at the NUTS2-level, based on equation 2. The regressions use a uniform kernel and varying bandwidths. Outcome variable: *GDP per capita growth*. 95% confidence intervals.

Figure A.15: Uniform Kernel: Effects on **Inequality of Household Incomes**



Notes: Coefficient plot of local linear bias-corrected fuzzy RD estimates with robust nonparametric standard errors, clustered at the NUTS2-level, based on equation 2. The regressions use a uniform kernel and varying bandwidths. Outcome variable: *Gini coefficient*. 95% confidence intervals.

D.3 Excluding Exceptions

As reported in Table A.2 above there is a small number exceptions to the 75% rule. A total of 15 observations are eligible for the policy despite having a GDP per capita that exceeds the threshold. If observations are treated as being ineligible even though they are eligible this can introduce a downward bias as the difference between treatment and control group diminishes. In the main text, we take this into account by estimating fuzzy RD regressions. An alternative approach is to exclude these exceptions from the analysis. In Table A.6 we implement this approach and replicate the baseline analysis while excluding these observations. As expected, the results are very similar but point to slightly larger point estimates, suggesting that, indeed, the exceptions reduce the size of the estimated effect. It also becomes visible that without the exceptions, sharp RD and fuzzy RD estimate the same effect size, because there are no non-compliers. We conclude that the findings are robust to excluding the exceptions.

Table A.6: Excluding Exceptions

Intention-to-Treat Effect *(Sharp RD)*	(1) GDP per capita	(2) Household income	(3) Gini
Above cutoff (75%)	-0.71	-0.46	-0.13
	(0.10)	(0.09)	(0.03)
Country FE and Year FE	✓	✓	✓
Observations	1262/3089	797/1615	832/1698

Local Average Treatment Effect *(Fuzzy RD)*	(1) GDP per capita	(2) Household income	(3) Gini
Eligibility	0.70	0.46	0.13
	(0.10)	(0.09)	(0.03)
Country FE and Year FE	✓	✓	✓
Observations	1261/3053	797/1615	832/1698

Notes: The sample excludes regions that are officially *eligible* even though they are above the cutoff. Otherwise, the specifications are identical to those reported in Tables 1 and 3.

D.4 Donut RD

In the main text we argued and provided evidence that sorting into treatment is unlikely to be an issue. Nevertheless, to be cautious we implement an alternative approach to address the concern that some regions might sort themselves into treatment. A frequently conducted robustness test in this context is the so-called Donut RD. The idea behind a Donut RD is that observations close to the cut-off might have the capacity to sort themselves across (or below) a given cut-off. To conduct a Donut RD the observations closest to the cut-off are excluded from the analysis and the models are then re-estimated while excluding these observations.

Columns 2-4 in Table A.7 reports the results of three Donut RD regressions that exclude observations that are 1, 2 or 3 percentage points above or below the cut-off. The results are very similar to the baseline estimate that is replicated in column 1 and thus robust to such a Donut RD approach.

Table A.7: 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. Otherwise, the specifications are identical to those reported in Table 1. Dependent variable: *GDP per capita growth*.

D.5 Including Regions with Fewer Survey Respondents

To address the concern that regional statistics could be distorted by an insufficient number of survey respondents per region and year we excluded observations with fewer than 50 survey respondents in the baseline. An alternative view could be that such an approach ignores valuable variation. This is why, in Table A.8, we re-estimate our models by including observations with less than 50 survey respondents within a region. Our results remain robust and are barely affected by this alternative approach.

Table A.8: Including Regions with Fewer Survey Respondents

Intention-to-Treat Effect *(Sharp RD)*				
	Mean	Mean	Gini	Gini
Above cutoff (75%)	-0.43	-0.28	-0.16	-0.13
	(0.14)	(0.14)	(0.03)	(0.03)
Country FE and Year FE	✓	✓	✓	✓
Observations	797/1638	808/1664	830/1710	841/1739
Sample restricted	✓	-	✓	-
Local Average Treatment Effect *(Fuzzy RD)*				
	Mean	Mean	Gini	Gini
Eligibility	0.50	0.33	0.19	0.16
	(0.16)	(0.15)	(0.03)	(0.03)
Country FE and Year FE	✓	✓	✓	✓
Observations	797/1638	808/1664	830/1710	841/1739
Sample restricted	✓	-	✓	-

Notes: If the sample is not restricted, it *includes* regions with less than 50 survey respondents. Otherwise, the specifications are identical to those reported in Tables 1 and 3.

E Surveys among Recipients: Additional Results

Table A.9 reports the full regression output of the analysis of self-reported personal benefits among survey respondents. Older respondents are less likely to report such benefits, consistent with an absence of labor market effects for retirees. Gender does not play a role.

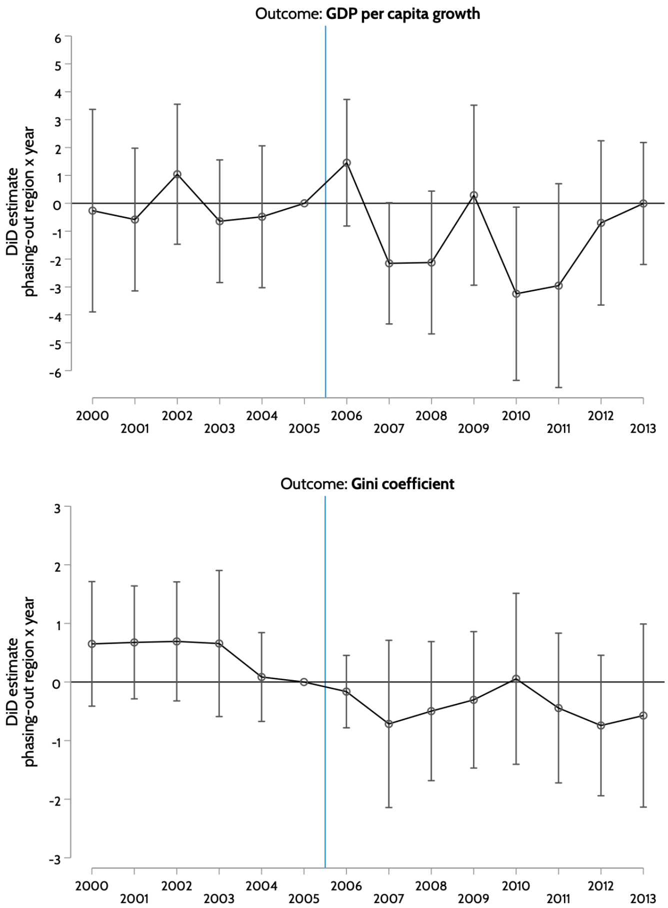
Table A.9: Self-reported Personal Benefit: Full Table

	(1)	(2)	(3)	(4)
Income	0.013	-0.001		
	(0.005)	(0.003)		
× EU funds		0.016		
		(0.003)		
Education			0.026	0.018
			(0.003)	(0.003)
× EU funds				0.008
				(0.003)
Heard of ERDF	0.127	0.126	0.114	0.114
	(0.020)	(0.020)	(0.020)	(0.020)
Heard of ESF	0.100	0.099	0.096	0.096
	(0.012)	(0.013)	(0.012)	(0.012)
Age	-0.002	-0.002	-0.002	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.000	-0.001	-0.002	-0.002
	(0.013)	(0.013)	(0.013)	(0.012)
Region FE	✓	✓	✓	✓
Regions	17	17	17	17
Observations	8451	8451	8451	8451

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.

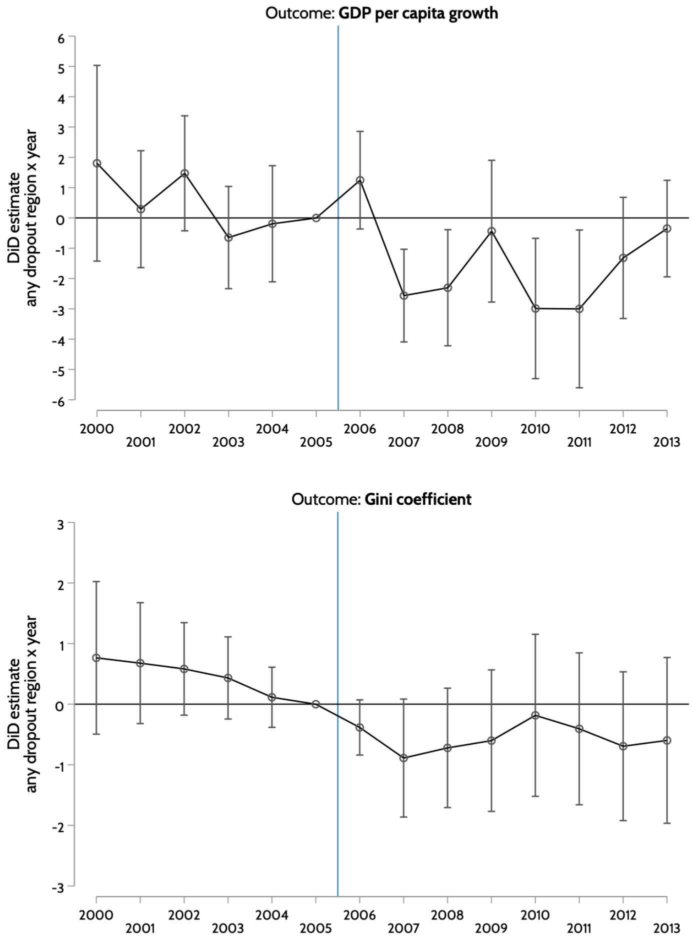
F DiD Design: Additional Results

Figure A.16: Event Study: Drop-Out Regions with **Transitory Support**



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). This model considers dropout regions with transitory *phasing-out support* as treated units.

Figure A.17: 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). This model considers *all* dropout regions as treated units.