WIFO ■ WORKING PAPERS
653/2022

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WIFO Working Papers 653/2022
November 2022

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2022/1/W/0

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Verlags- und Herstellungsort: Wien

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Abstract

We present a novel approach for analyzing the effects of EU cohesion policy on local economic activity. For all municipalities in the border area of the Czech Republic, Germany and Poland, we collect project-level data on EU funding in the period between 2007 and 2013. Using night light emission data as a proxy for economic development, we show that the receipt of a higher amount of EU funding is associated with increased economic activity at the municipal level. Our paper demonstrates that remote sensing data can provide an effective way to model local economic development also in Europe, where no comprehensive cross-border data is available at such a spatially granular level.

JEL Classification: R11, O18, H54

Keywords: Regional Development, EU Cohesion Policy, Remote Sensing

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We thank the Bertelsmann Foundation for financial support. We thank Elisabeth Arnold, Peter Reschenhofer, Maria Riegler, Theresa Schröter, Jelena Todorovic and Diego Alonso Alarcón Díaz for excellent research assistance. Furthermore, we are grateful for helpful comments and suggestions by Katharina Gnath, Natascha Hainbach and Peter Mayerhofer.

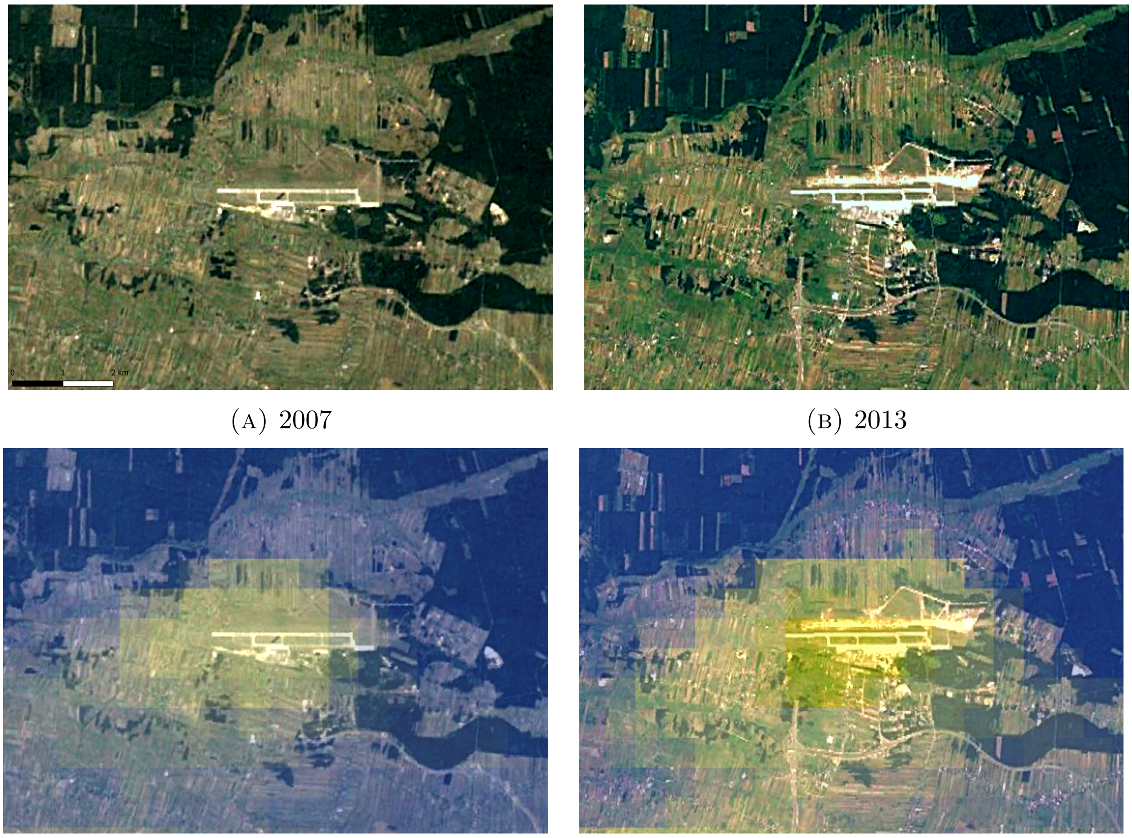
1 Introduction

A key priority of the European Union is the promotion of economic and social cohesion among its regions. As of today, cohesion policy constitutes the second-largest item of the EU's budget. However, despite its financial relevance, there exists no clear consensus in the literature about the effectiveness of EU cohesion policy in promoting economic development. One reason for the lack of clear-cut empirical evidence is that data on EU funding is typically aggregated and only available at the level of NUTS-2 or NUTS-3 regions. For an assessment of its local effects within larger geographical units, including the question what type of funding is particularly supportive of regional economic activity, it is necessary to exploit more disaggregated data.

Our paper presents a novel approach for estimating the effect of EU cohesion policy on economic activity: First, we draw on a new and unique project database containing the detailed distribution of EU funds spent in local administrative units (LAUs), i.e., the municipalities and communes of the European Union. Second, we leverage the potential of remote sensing data, as many EU member states lack information on GDP or other (comparable) measures of economic activity at the municipal level. Guided by the hypothesis that increased economic growth is accompanied by changes in spatial-structural parameters, we overcome this data limitation by using changes in municipality-level night light emissions to proxy the development of local economic activity.

Combining both data sources, we estimate the effect of EU regional funds on economic activity for a region in the border area of the Czech Republic, Germany and Poland for the programming period 2007-2013. We choose this region due to its large variation in EU funding activity across municipalities, and because high-resolution satellite images are available for a long period of time. To the best of our knowledge, this paper is the first to analyze EU cohesion policy at such a spatially granular level, covering a large set of administrative units in three EU member states. Because we observe more than 6,500 municipalities, we can flexibly control for time-constant regional characteristics by including fixed effects at the level of NUTS-2 or NUTS-3 regions. In particular, including these fixed effects eliminates the institutional link between economic growth and the receipt of EU funding, which arises as NUTS-2 regions with GDP per capita of less than 75% of the EU average become eligible for the convergence objective and receive more funding. Furthermore, we establish stylized facts concerning the distribution of EU regional funds and document the relationship between economic activity and EU funding by funding objective.

As an illustrative example, Figure 1 shows the airport of Katowice, Poland, where an EU-funded expansion and modernization of the infrastructure took place between 2007 and 2015. Panels (A) and (B) show the airport before and after the construction work in 2007 and 2013, respectively. Further infrastructural development is visible around the airport as well, including more road infrastructure and built-up structures. This detailed view reveals how this particular project has triggered a landscape change linked to economic development. When comparing the amount of night light emissions in 2007 and 2013 in the area (Panels C and D), local developments can be directly linked to changes in the satellite data. The creation of a new runway as well as infrastructure developments and built-up structures in the south of the image led to an increase in night light emissions, while emissions in the agricultural and forest areas remained relatively stable.



(A) 2007

(B) 2013

(C) 2007

(D) 2013

Figure 1 – EU-funded Expansion and Modernization of the Airport Katowice, Poland

Notes: The images show the expansion and modernization of airport and port infrastructure north of Katowice, Poland, as seen from high resolution optical Landsat-5 satellite imagery (images A) and B). The images were taken in 2007 and 2013, respectively. Images C) and D) show night light emissions before and during construction period. Low emissions are indicated by blue colored overlay, yellow colors indicate high night light emissions.

Our results can be summarized as follows. First, within a given NUTS-2 or NUTS-3 region, funding is—ceteris paribus—more likely to flow to municipalities that exhibit a higher level of initial night light emissions. Keeping this measure of initial economic activity constant, funding is more likely to flow to municipalities with a higher population and lower levels of cropland. This likely reflects agglomeration effects and the role of favorable ecosystems (in cities) for attracting more EU funds.

Second, we describe systematic differences in the quantity and types of funding across countries. For example, municipalities in Poland carried out much larger individual projects than municipalities in Germany or the Czech Republic. This can be explained by the fact that the lion's share of funding in Poland was directed at the creation of new transport infrastructure like roads or railways, which constitutes a particularly costly type of project.

Third, municipalities which received more EU funding experienced a significantly stronger increase in night light emission during the programming period. The association between funding and growth in night light emissions turns out to be higher when spill-over effects from neighboring municipalities are taken into account. While our analysis, as much of the prior literature, cannot rule out all confounding factors and therefore may not deliver an unbiased estimate of the effect of receiving regional funds on local growth, we document a stable and robust positive association between the amount of funds received and an increase in night light emissions.

Our paper contributes to two strands of the literature. First, we contribute to the literature on the economic growth effects of EU cohesion policy. Previous studies have drawn differing conclusions concerning its effectiveness. While most papers report a positive association between funding and growth (see, e.g., Cappelen et al., 2003; Rodríguez-Pose and Fratesi, 2004; Beugelsdijk and Eijffinger, 2005; Becker et al., 2010; Pellegrini et al., 2013; Becker et al., 2018; Cerqua and Pellegrini, 2018a), others have found insignificant or even negative effects (see, e.g., Dall'Erba and Le Gallo, 2008; Fagerberg and Verspagen, 1996). A meta-analysis by Dall'Erba and Fang (2017) finds estimated growth elasticities which are on average positive, but close to zero.

A common finding, though, is that there is substantial regional heterogeneity in the success of EU cohesion policy, mirroring the fact that its implementation should not follow a "one size fits all" approach, but should take into account local conditions. Characteristics found to be relevant for the policy's success in increasing economic growth are usually measured at the NUTS-2 level and include human capital endowments in a region (e.g. Becker et al., 2013), institutional quality (e.g. Rodríguez-Pose and Garcilazo, 2015) and territorial capital (Fratesi and Perucca, 2014). Most of these previous studies do not consider the broad variety of policy actions and objectives addressed by EU cohesion policy in each and every region, and the variation in policy actions and objectives across and within

Member States.[1] There are only a few studies which follow a similar approach to ours, albeit focusing on only one EU member state: Mayerhofer et al. (2020) analyze European Structural and Investment Funds in Austria at the municipality-level using project-level data provided by Austrian authorities. Cerqua and Pellegrini (2018b) study the effect of EU cohesion policy for Italian regions using project-level data at the municipality level, with conclusions drawn for a less granular regional level.[2]

We conduct a more fine-grained analysis of cohesion policy spending, namely at the sub-regional level of municipalities across several countries. Our results show that not only (NUTS-2) regional but also local characteristics as well as the type of projects selected for implementation in a municipality play a role for policy effects. This intra-regional perspective has been shaded in most previous research. Hence, our study contributes to a better understanding of the differential regional policy effectiveness.

Second, our paper relates to a growing literature which documents how remote sensing data can be used to evaluate place-based economic policies (for a review see Donaldson and Storeygard, 2016). Most prominent are applications where GDP growth has been proxied by night light emissions (e.g. Jean et al., 2016; Mellander et al., 2015), as in this study.[3] For instance, remote sensing data has been used to delineate economically strong regions (Florida et al., 2008; Taubenböck et al., 2017; Georg et al., 2018) or with the underlying aim of analyzing real regional GDP without any measurement errors (Gennaioli et al., 2014). However, most of these studies focus on the comparison of larger administrative units such as countries (Henderson et al., 2012) or NUTS-1 regions in Europe (Lessmann and Seidel, 2017). In contrast, our study focuses on a much finer level of spatial detail.

The remainder of this paper is organized as follows. Section 2 describes the data and the methodology. Section 3 documents the spatial distribution of EU funding among the municipalities of the sample region. In Section 4, we present our results on the association between EU funding and night light emission growth. Section 5 summarizes our findings and discusses how our insights may prove valuable for future research.

[1]Rodríguez-Pose and Fratesi (2004) point to different impacts of types of policy actions on economic growth. Mohl and Hagen (2010) differentiate between the effects of Objective 1 and other cohesion policy spending.

[2]Moreover, exploiting micro-level data at the beneficiary level for more than one country, Bachtrögler et al. (2020) investigate the effects of structural funds on the performance of supported manufacturing firms in seven EU member states and find that the effects differ across countries, types of regions and firm-level outcome indicators.

[3]Many prior studies using night lights focus on developing countries, where GDP estimates may be unreliable even at the federal or state level. In this paper, we use night lights to fill a different type of data gap: While in Europe information on GDP and other central indicators is available up to the NUTS-3 level, there is no (cross-border) information available at the more granular municipality level. Moreover, granular national accounts data is only released with a significant time lag of several years. Accessing real time satellite imagery therefore also provides an advantage for policy analysis.

2 Institutional Setting and Data

2.1 Institutional Setting

EU cohesion policy aims at reducing economic and social disparities across the regions of the European Union. According to the ex-post evaluation of the 2007-2013 programming period,[4] 346.5 billion Euro were distributed through the European Regional Development Fund (ERDF), the European Social Fund (ESF) and the Cohesion Fund (CF). These funds co-finance investments of beneficiaries like firms or local authorities in different domains. The majority of funding is directed to less developed regions—i.e. NUTS-2 regions with a GDP per capita below 75% of the EU average across a three-year period prior to the programming period—under the so-called Convergence Objective. Eligible for funding by the CF instead are only EU member states with a gross national income below 90% of the EU average, which means that Germany is not a recipient country for CF funding. The remaining funds were allocated under the objective of regional competitiveness and employment, and territorial cooperation (through INTERREG(ional) programs).

In the first step, the national strategic reference framework, designed by the member states and confirmed by the European Commission, defines priorities and targets of cohesion policy in the seven-year programming period ahead. Subsequently, operational programs are designed to address these priorities, either at the regional or national level, for the latter mostly with a thematic focus such as transport or environment. The respective regional or national managing authorities also define project selection criteria on which funding decisions for specific projects shall be based. Beneficiaries can then apply with their intended projects for co-financing by one of the funds.

Since the 2007-2013 programming period, information on these projects and corresponding beneficiaries has to be provided publicly by the managing authorities. Because there exists no official and unique database including project-level information provided by European institutions, we collect this data from individual lists of beneficiaries.

2.2 Data

We link project-level information on EU funding and remote sensing data at the most granular spatial unit possible, which is the level of Local Administrative Units (LAU). Local Administrative Units, referred to as municipalities henceforth, are the smallest entities within the NUTS scheme and represent municipalities and communes of the European Union.

[4]See https://ec.europa.eu/regional_policy/en/policy/evaluations/ec/2007-2013/.

We collect data for the border region between the Czech Republic, Germany and Poland. Thus, the sample region comprises less developed NUTS-2 regions (all Polish and Czech regions, and some regions in Germany, e.g. Chemnitz and Mecklenburg-Vorpommern) and regions with a relatively high GDP per capita as compared to the EU average (in Bavaria, Germany). Furthermore, the sample region consists of both urban centers (such as Wrocław, Poland, or Dresden, Germany) and rural areas, which allows us to exploit rich variation in EU funding within and across NUTS-2 regions. Figure 2 depicts the sample region. While the investigated region comprises 17 NUTS-2 regions and 102 NUTS-3 regions, it consists of 6,555 municipalities.[5]

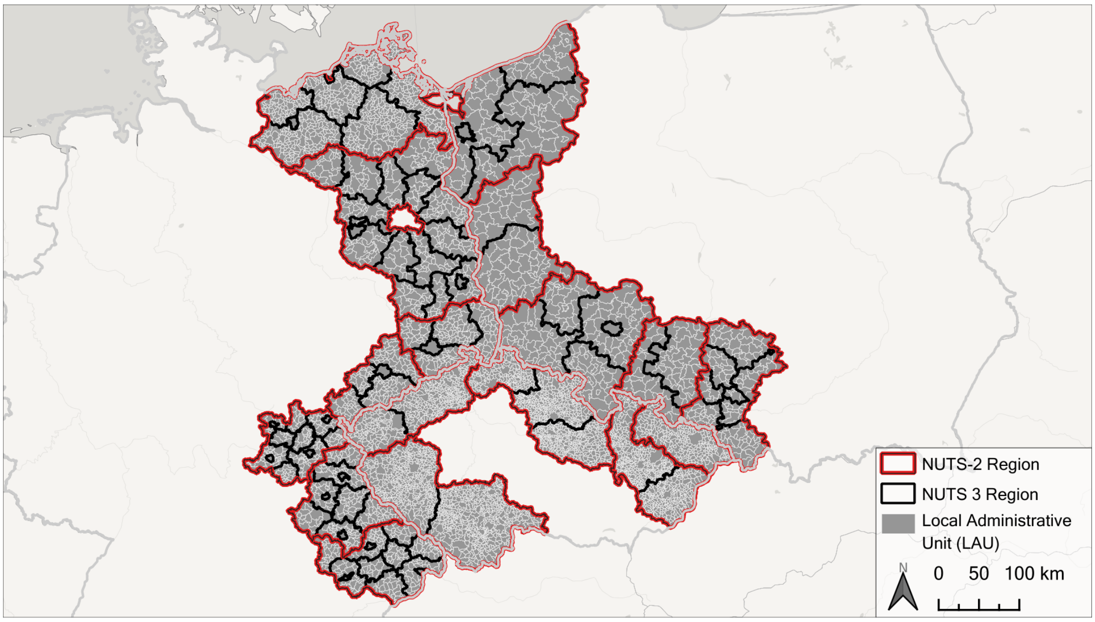


Figure 2 – Overview of the Sample Region

Notes: This figure shows NUTS-2 and NUTS-3 regions as well as Local Administrative Units in the border region between the Czech Republic, Germany and Poland.

Data on EU Funding. As policy variable of interest, we explore EU support provided via the ERDF and CF. Projects co-financed by the ESF are not considered, as information on the exact location of a large share of final beneficiaries (often individuals) is not

[5]From initially 6,571 municipalities, we exclude 16 uninhabited military training grounds with own municipal status in Germany and the Czech Republic. Note also that although Eurostat aims to provide a framework of comparable spatial units, municipalities in the different member states vary substantially in size. Figure A.1 in the Appendix shows the distribution of municipality size in the sample region, indicating a relatively high spatial segmentation in the Czech Republic. Polish municipalities are largest in terms of square kilometers. Our sample consists of 3,733 municipalities in the Czech Republic, 2,220 German and 602 Polish municipalities.

available. In addition, ESF projects, such as training or labor market measures, are expected to be less visible in space than, for example, infrastructure projects co-financed by the CF or ERDF. We retrieve project-level data on ERDF and CF support from lists of beneficiaries provided by the managing authorities, as well as for INTERREG projects (in cross-border, transnational and interregional co-operation programs, part of ERDF) from the KEEP database.[6] The methodological approach for data collection and cleaning is based on Bachtrögler et al. (2021),[7] and described in more detail in Appendix A.3.

While the CF focuses on fostering network infrastructure in transport and energy as well as environmental protection, there is a growing focus of the ERDF on supporting research and innovation as well as increasing the competitiveness of small and medium-sized enterprises. Figure 3 shows the thematic distribution of ERDF and CF co-funding in our sample region.[8] More than a quarter of the funds registered for the sample region is targeted at transport infrastructure projects. In particular in the Czech regions, a bulk of the ERDF and CF funding is devoted to this category, as well as to environmental infrastructure. In the Polish regions, almost half of funding is directed at network infrastructures in transport and energy. In the German regions, the largest share of ERDF funding is targeted at productive investment and business support.

We enrich this data set with geographic information on the location of each project. As the degree of geographical detail provided varies across countries, we use different methods for geolocalization. Appendix A.3 explains how municipality codes were assigned to projects, and Appendix Table A.2 demonstrates the success of this exercise by comparing the funding amounts considered in this analysis compared to aggregated official numbers. If the project location is not reported by the managing authorities, we use the headquarter location of the beneficiary firm or organization in case of direct grants to firms or organizations. The amount of EU funding for INTERREG projects, as well as for other projects carried out in more than one municipality, is divided uniformly by the number of municipalities in which project partners are located and the project is implemented, respectively.

Remote Sensing Data. At the municipality level, no GDP data or other comparable information on economic development is available in our sample region. Therefore, we use night light emissions as a proxy for changes in local economic activity. Night light

[6]See https://keep.eu/.

[7]See also Bachtrögler et al. (2019) for previous work on 2007-2013 project-level funding data.

[8]Thematic categories are assigned to Czech and Polish projects based on the specific priority of the operational program to which each project corresponds to. For German projects, categories are assigned based on a learning sample generated by manual categorization of projects considering project descriptions, and in the following using a Naive Bayes classifier (as well as manual checks). For INTERREG projects, the (first) thematic objective is considered to assign a thematic category.

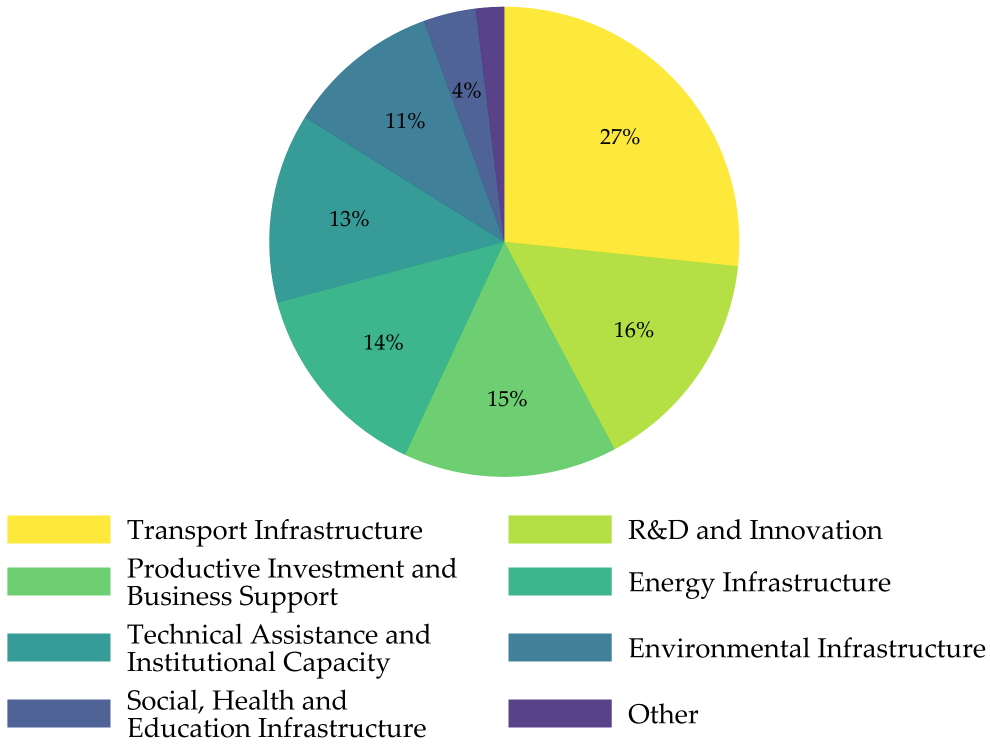


Figure 3 – Distribution of ERDF and CF Co-funding by Thematic Categories

Notes: This Figure shows the distribution of ERDF and CF co-funding in the sample region by broad funding categories. See Table A.2 in the Appendix for details on overall funding amounts.

emissions have been associated with urban and regional economic development in previous studies (Zhu et al., 2017; Wu and Wang, 2019), and fulfill key requirements for suitable satellite images. They provide meaningful features for quantifying human made local environmental change, and are available as consistent time series and for the whole sample region. Moreover, there is unrestricted and free data access and open data license.

We use data from the "Defense Meteorological Satellite Program Operational Linescan System" (DMSP-OLS), which is the only sensor that provides uninterrupted coverage of global night light imagery for the period 2007-2013. In Appendix A.2, we describe the preprocessing steps applied to the raw data. In addition, we use land cover data derived from the MODIS sensor, which allows us to observe changes in land cover during our observation period. In order to match the remote sensing data with the project-level database on a common spatial level, we aggregate all datasets to the spatial unit of municipalities (LAUs). Deriving municipality-based statistics for satellite imagery involves compiling zonal statistics for each municipality, i.e., arithmetic aggregates of the image data within each spatial administrative unit.

To test the viability of these data for our research question, we first assess the strength of the association between economic growth and night light emissions. This is done by aggregating night light emissions from the municipality level to the NUTS-3 level, where information on nominal GDP is available. Appendix Table B.1 shows the results of a regression of GDP growth on the growth of total night light emissions at the NUTS-3 level. In the period 2007 to 2013, a 10% increase in night light emissions was associated with a 1.70% increase in GDP, which rises to 1.95% when accounting for NUTS-2 fixed effects. Our estimates are consistent with prior literature (Henderson et al., 2012; Lessmann and Seidel, 2017), pointing out that night light emission is a good proxy for GDP also in our setting. For the interpretations of our results, we will later make the (untestable) assumption that this relationship also holds at the municipality level.

Summary Statistics. Table 1 depicts summary statistics for the main variables used in our analysis at the level of municipalities.

	Mean	Median	SD	Min	Max
Number of Projects	17	3	74	0	3,189
Funding Amount (in TEUR)	4,379	150	24,988	0	877,201
Total Night Light Emission	4,375	1,706	8,253	49	179,912
Growth Night Light Emission	-0.5%	-1.7%	25.0%	-176.4%	212.0%

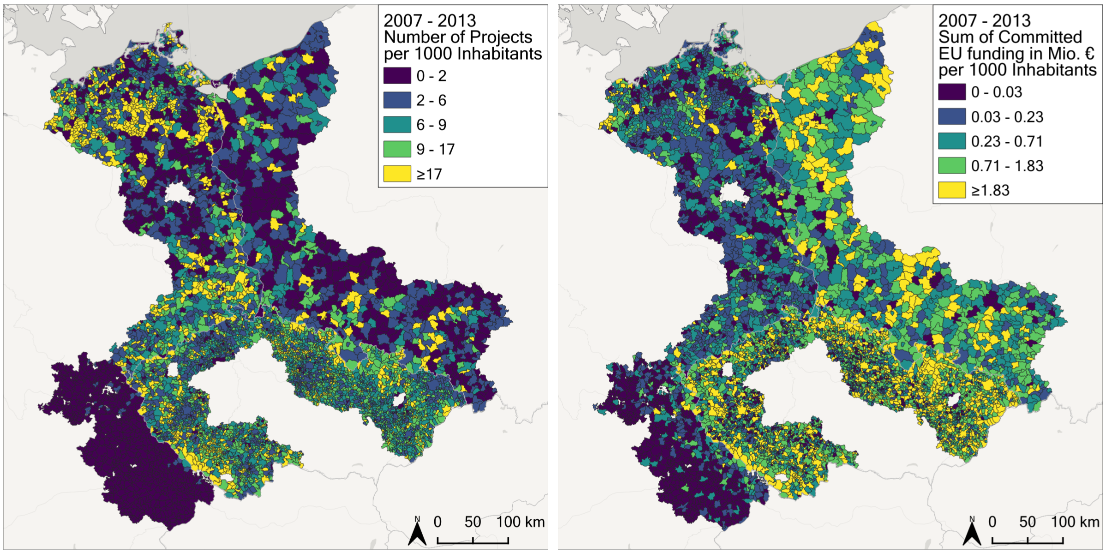
Table 1 – Summary Statistics by Municipality

Notes: This table displays summary statistics for the number of projects, the funding amount (in 1,000 Euro), the aggregated total night light emission and the growth of night light emission per municipality. All statistics refer to the whole funding period 2007-2013. Total night light emissions are registered as digital numbers (DN, 0 to 63) by the DMSP-OLS sensor.

3 Spatial Distribution of EU Regional Funds

The data set of co-funded projects generated for this paper allows for localizing ERDF and CF funding at the municipality level. To the best of our knowledge, we are the first to document and analyze the distribution of regional funds on such a fine geographical level of aggregation for more than one country. Moreover, our data set makes it possible to differentiate the analysis in terms of thematic categories, and to document which municipalities in our sample region invested how much of EU funding in which area.

Figure 4 maps the intensity of EU funding received in the 2007-2013 programming period in terms of the number of projects carried out in a municipality, and the amount of EU funding allocated to each municipality at current prices.[9] The total number of projects implemented in a municipality in the sample region ranges from 0 to 3,189 (Table 1). The distribution of projects among municipalities is skewed: The average amounts to 17 projects in one municipality, while half of municipalities considered carried out three or fewer projects. The highest number of projects in our sample is documented for the German cities of Dresden and Chemnitz.



(A) Number of Projects (B) Sum of Committed Funding

Figure 4 – Number of Projects and Sum of Committed Funding

Notes: This figure shows heat maps of the number of projects (Panel A) and the sum of committed funding (Panel B) for all municipalities in the sample for the years 2007-2013. The colors represent quintiles of the distribution of the respective variable.

The mean funding amount per project in a municipality in our sample amounts to 261,190 Euro. As Panel (B) of Figure 4 shows, there is a large dispersion of funding amounts across and within countries. While the mean funding amount per project is 112,670 Euro in the German municipalities and 295,480 Euro in the Czech municipalities, it is much higher in the Polish municipalities with 400,800 Euro. The higher amount in Poland may be explained by the fact that most funding is attributed to (large) energy and transportation infrastructure projects. However, this is also true for Czech regions, with major funding allocated to transportation and environmental infrastructure. Therefore, not only the funding principles as well as project selection and organization are expected

[9]Note that for the analysis of the number of projects, a project implemented in more than one municipality is counted as one in each municipality. The EU co-funding amounts are divided according to the number of municipalities involved.

to differ across member states (e.g. allocation of funds for one infrastructure project to one provider or in tranches to more than one provider), but also the reporting procedures.[10]

When analyzing absolute funding amounts received, the different size of municipalities across countries needs to be taken into account as they are significantly larger in terms of area and population in Poland than in Germany and—especially—in the Czech Republic. The three municipalities in receipt of the highest funding levels in the sample region are Dresden, Germany, Wrocław, Poland, and Ostrava, Czech Republic. All three are large cities where economic activity is concentrated, indicating an agglomeration advantage in attracting EU funding.

In Table 2, we present the results of a regression analysis exploring the relationship between the amount of funding received and various municipality characteristics. First and foremost, we include the initial level of night light emissions in 2007—that is before municipalities received funding—to investigate whether funding is more likely to flow into economically weak (low level of night light emission) or strong (high level of night light emission) municipalities. Moreover, we add the population in a municipality as well as its (initial) land cover, modeled by the share of a municipality defined as urban or as cropland according to the MODIS classification. We consistently account for fixed effects at the level of countries and NUTS-2 regions to capture the fact that under the relevant funding regulation, economically less developed NUTS-2 regions deliberately received higher funding amounts. However, below the NUTS-2 level, no clear allocation rules exist regarding how funding should be distributed between municipalities.

The result of this analysis suggests that the sum of ERDF and CF funds allocated to municipalities is directly linked to the initial level of economic activity, measured in terms of the sum of night light emissions in 2007. This finding indicates that, within our sample region, higher amounts of funding are allocated to cities and communes enjoying relatively high level of economic activity before receiving the funds. Column (4) of Table 2 indicates that 1% higher initial night light emissions are associated with a rise in the EU funding amount by around 1.6% over the period 2007-2013. This effect drops to 0.6%, but remains significant, when controlling for population size in Column (5), which turns out—as expected—as an important determinant of the funding amount received. In addition, funding amounts are lower in municipalities with a higher share of cropland.

These findings are consistent with the funding principles of the ERDF in particular, which is mainly directed at productive investment and business support, as well as at R&D and innovation. After all, urban municipalities where many firms are located and population is higher are likely to profit from agglomeration effects and synergies and thus attract more funds than regions with relatively little economic activity. Furthermore, the

[10]See Bachtrögler et al. (2019) for an exploration of the determinants of project size in projects co-funded by regional funds in 2007-2013.

	(1) Funding	(2) Funding	(3) Funding	(4) Funding	(5) Funding
log(NLE_{2007})	2.012***	1.798***	0.650***	1.645***	0.595***
	(23.73)	(19.50)	(5.87)	(16.57)	(4.56)
log(Population)			1.175***		1.179***
			(9.01)		(6.75)
Share Urban_{2007}				3.303***	-0.282
				(5.73)	(-0.34)
Share Cropland_{2007}				-1.021***	-1.060***
				(-3.50)	(-3.98)
Country FE	✓	-	-	-	-
NUTS-2 FE	-	✓	✓	✓	✓
Observations	6555	6555	6555	6555	6555

Table 2 – Relationship Between EU Funding and Night Light Emissions, Conditional on Local Characteristics

Notes: This table reports the estimates of an OLS regression of total ERDF and CF co-funding amounts in the period 2007-2013 on the sum of night light emissions in a municipality, land cover at the beginning of the programming period (2007) as well as population. The inverse hyperbolic sine transformation was applied to the funding amount (in current prices) and population. Column (1) includes country fixed effects, Columns (2), (3), (4) and (5) NUTS-2 fixed effects. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

allocation is likely driven by a higher absorptive capacity of urban centers, i.e., better human capital and institutional as well as administrative capacities to successfully apply for funding. For the CF, the result appears less intuitive, as it mainly targets infrastructure projects, which could also be based in rural areas. Separate regressions for ERDF and CF funding intensity indeed confirm that there is no statistically significant link between initial economic activity and CF funds allocated to a municipality when controlling for population.

4 Regional Funds and Economic Performance

4.1 Estimation Strategy

To analyze the effects of EU cohesion policy on growth, one would ideally like to randomly allocate funding across municipalities or regions, so that the funding effect would be independent of any other factors accounting for growth rate differentials. In reality, instead, most of the funds are explicitly targeted at economically less-developed NUTS-2 regions.[11] The key strength of our research design is the ability to observe variation in EU funding *within* NUTS-2 (and NUTS-3) regions, which allows us to break the mechanical endogeneity of funding and economic growth by including fixed effects at the level of NUTS-2 (NUTS-3) regions. In all of our analysis, we thus compare whether municipalities within a given NUTS-2 (or NUTS-3) region that received comparatively more funding grew stronger.

However, even within a given NUTS-3 region, it is likely that the EU funding amount committed to a municipality depends on regional and local characteristics, such as administrative capacity or the presence of innovative actors to develop projects and successfully apply for funding. As shown in Section 3, funding is more likely to flow into municipalities with high initial night light emissions and also varies with the proportion of urban and rural area. To account for these factors, we control for the initial night light emissions in 2007, the share of urban area, the share of cropland and log population, all at the municipality level.[12] Formally, we estimate the following equation

$$\Delta NLE_{i,j} = \beta_0 + \beta_1 Funding_{i,j} + \beta_2 X_{i,j} + \phi_j + \varepsilon_{i,j}, \tag{1}$$

where for each municipality i in NUTS-2 region j the growth in night light emissions ΔNLE is explained by the funding received, a vector X_i with municipality level controls, and a set of NUTS-2 fixed effects ϕ_j. The growth in night light emission is defined as $\Delta NLE = ln(NLE_{t_1}) - ln(NLE_{t_0})$, meaning that we compute it as the log difference between night light emission in the last and the first year of the programming period. If funding is uncorrelated with economic conditions once we control for these characteristics, β_1 uncovers the causal effect of EU funding on the growth of total night light emissions. However, in our setting, we cannot verify that this is indeed the case as further unobservable factors may be important. For this reason, our results should be interpreted as correlations. In that sense, our results answer the question whether municipalities that received more funding grew stronger—and not necessarily to what extent the funding *induced* them to grow stronger.

Our analysis mainly measures funding via the total funding amount that a municipality received in the funding period. As the distribution of funds is highly skewed, we employ

[11] E.g. Becker et al. (2010) have exploited the cut-off point of regional GDP per capita below 75% of the EU average (in pre-defined years), which determines the eligibility of less developed regions for funds under the Convergence objective, for the estimation of causal policy effects in those regions.

[12] As population at the LAU level is not provided on a regular yearly basis by Eurostat, we use the population for the year 2018, which is consistent with the administrative boundaries used in our analysis. However, results are virtually unchanged if we use 2001 or 2011 as the base year instead.

an inverse hyperbolic sine transformation for our baseline estimates.[13] As a robustness check, we also use the logarithm of the funding amount (dropping municipalities which received no funding at all) and the total number of projects each municipality received over the funding period as alternative policy measures. Standard errors are clustered at the level of NUTS-3 regions.

4.2 Baseline Results

Table 3 shows our baseline results. In Column (1), we control for the initial night light emissions in 2007 to clean our estimates from potential convergence effects, and employ NUTS-2 fixed effects. Hence, we compare how the growth rate of night light emission varies at the municipality level within a certain NUTS-2 region as a reaction to the funding received, holding initial night light emissions fixed. We estimate a coefficient of 0.0074, meaning that a 1% increase in EU funding is ceteris paribus associated with a 0.007 percentage points higher growth rate in night light emission. This estimate decreases when additionally controlling for log population and the respective proportions of urban area and cropland at the start of the funding period, but barely changes when employing fixed effects at the more fine-grained level of NUTS-3 regions.[14] In Column (4), where we estimate the most comprehensive model, the funding coefficient is estimated at 0.0033. For the average municipality within our sample region worth which receives funding worth 625,500 Euro, we thus find that total night light emission increases by 0.05%.

What does this tell us about the association between funding and GDP growth? Under the assumption that the relation between night light emission and funding at the LAU level is not different from the relation at the NUTS-3 level, we can scale the estimated growth effects with the GDP/nightlight emission correlation as found in Column (2) in Appendix Table B.1. Doing so, we find that the funding amount flowing into the average municipality is associated with an increase in GDP by 0.01%.

We also find a positive and significant association with night light emission growth if we use the number of projects that were funded in the period 2007-2013 as the main regressor instead of the total funding amount (Appendix Table B.3). Estimates approximately dou-

[13]Researchers often use the log transformation to deal with right skewed distributions like income, wealth or investment. However, this is not possible in the presence of many zeros, as $ln(0)$ is not defined. An alternative is the inverse hyperbolic sine transformation (IHS), defined as $ln(x + \sqrt{x^2 + 1})$, which has very similar properties as a standard log: it equals 0 when $x = 0$ and its slope tracks the slope of $ln(x)$ more closely than $ln(1 + x)$ when x is small. Except for very small values of y, the variable transformed via IHS can be interpreted in exactly the same way as a standard logarithmic transformation.

[14]While using NUTS-3 fixed effects eliminates additional time-constant potential confounders, we also lose a few observations in the estimation as some municipalities also constitute a NUTS-3 region. For example, the German cities of Dresden and Leipzig form standalone NUTS-3 regions. Due to this small sample selection, we do not focus on one single preferred specification but consistently report estimates for all four specifications.

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
Funding Amount	0.00742***	0.00325**	0.00745***	0.00334**
	(4.50)	(3.07)	(4.38)	(3.03)
$\log(NLE_{2007})$	-0.0664***	-0.181***	-0.0694***	-0.184***
	(-4.34)	(-5.89)	(-4.46)	(-5.89)
Share Urban$_{2007}$		-0.281***		-0.278***
		(-5.90)		(-5.49)
Share Cropland$_{2007}$		-0.127***		-0.136***
		(-5.09)		(-5.08)
log(Population)		0.126***		0.126***
		(5.99)		(5.95)
NUTS-2 FE	✓	✓	-	-
NUTS-3 FE	-	-	✓	✓
Observations	6555	6555	6555	6555

Table 3 – Night Light Growth and Funding Amount

Notes: This table reports the estimates of a regression of the growth in log night light emission in the period 2007-2013 on the total funding amount received by each municipality (transformed using the inverse hyperbolic sine transformation) and controls. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. Columns (1) and (2) include NUTS-2 fixed effects, Columns (3) and (4) NUTS-3 fixed effects. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

ble when only considering the intensive margin (by using the log transformation instead, see Appendix B.2).

4.3 Accounting for Spatial Spillovers

Our estimation approach takes advantage of the spatial disaggregation of our funding data, leading us to observe funding and outcomes at the granular municipality level. As previously discussed, this strategy eliminates several problems prior literature has been facing. However, on such a fine-grained level of analysis, spatial spillover effects are also more likely to occur. In the example of Katowice in the introduction, the airport expansion appears to have brought substantial economic benefits for Katowice itself. In addition, though, it is likely that adjacent municipalities profited as well from easier accessibility. This line of reason also applies to smaller projects, such as the construction of roads, which cut commuting times for inhabitants of neighboring municipalities. Such spillover effects do not always have to be positive: Imagine the EU funding supports the development of a commercial area in municipality A. Theoretically, this could incentivize firms from a neighboring municipality B to relocate to municipality A. In this case, B would lose from the funding in A, implying a negative spillover.

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
Funding Amount	0.00699***	0.00274**	0.00714***	0.00300**
	(4.69)	(2.87)	(4.54)	(2.89)
Funding Amount in Neighboring Municipalities	0.00362	0.00419*	0.00425	0.00465*
	(1.71)	(2.39)	(1.79)	(2.44)
$\log(NLE_{2007})$	-0.0685***	-0.184***	-0.0722***	-0.188***
	(-4.33)	(-5.89)	(-4.44)	(-5.90)
Share Urban_{2007}		-0.282***		-0.282***
		(-5.98)		(-5.57)
Share Cropland_{2007}		-0.124***		-0.134***
		(-5.14)		(-5.16)
log(Population)		0.127***		0.127***
		(6.00)		(5.95)
NUTS-2 FE	✓	✓	-	-
NUTS-3 FE	-	-	✓	✓
Observations	6555	6555	6555	6555

Table 4 – Funding Effect Including Spillovers

Notes: This table reports the estimates of a regression of the growth in log night light emission in the period 2007-2013 on the total funding amount received by each municipality (transformed using the inverse hyperbolic sine transformation) and controls. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. The variable *funding in neighboring municipalities* is computed as the sum of funding received by all neighboring municipalities (and transformed as funding received by each municipality) and indicates the size of spillover effects. Columns (1) and (2) include NUTS-2 fixed effects, Columns (3) and (4) NUTS-3 fixed effects. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To test for spillover effects, in Table 4 we re-estimate our baseline specification but additionally control for the funds flowing into neighboring municipalities. To do so, we define a variable measuring the total funding amount received by all municipalities that share a direct border with the municipality under consideration. This variable accounts for spatial spillover effects. Regardless of the specification used, the coefficient of this variable is positive and statistically significant. This demonstrates that spillover effects are present and on average positive. If this variable would fully capture the spillover effect, the total funding effect would be the sum of both coefficients. For example, the funding effect in specification (4) is 0.00300+0.00465=0.00765, as compared to an estimate of 0.00334 in Table 3. This indicates that the more naive estimation in Table 3 will structurally underestimate the total treatment effect in the region.

4.4 Heterogeneity

A key feature of our dataset is the possibility to differentiate between types of funds and between funding objectives. In the following, we present evidence for the heterogeneity of the relationship between different types of funding and growth in local economic activity.

Heterogeneity by Funding Categories. As described earlier, remote sensing data may vary in their ability to capture the impact of different projects, depending on the funding category. For example, we would expect that funds directly aimed at visible changes on the earth surface, like the bulk of infrastructure projects, are easier to spot from space than projects dedicated to foster education or social cohesion. Figure 5 shows that the funding effect indeed varies substantially by project category. For the categories *ICT Infrastructure*, *Employment*, *Social Inclusion*, *Technical Assistance and Institutional Capacity*, as well as *Environmental Infrastructure*, the funding effect is insignificant. In contrast, there is a significantly positive relationship between the change in local economic activity and EU funding in the categories *Productive Investment and Business Support*, *Environmental Infrastructure*, *Transport Infrastructure* and *Social, Health and Education Infrastructure*, which all are expected to leave visible changes on the ground. Considerable significant coefficient estimates are also found for the categories *Education and Training* as well as *R&D and Innovation*, much of which is targeted at research infrastructure. While this is in line with previous studies, it is remarkable that we see such a strong effect on changes in night lights, as it could be assumed that this type of funding would be less reflected in changes in the landscape than infrastructure projects. Possibly, this could indicate further private investments following the initial funding.

Heterogeneity by Type of Fund. We furthermore compare the funding effect by the type of fund, keeping in mind that the municipalities considered in Germany by design do not receive CF funding. As in the results in Table 3, we control for the number of inhabitants, land cover and initial night light emissions, and in this case run three separate regressions considering the specific amounts per type of fund. Figure 6 shows that the funding is statistically significantly linked to local economic development when considering projects co-funded by the ERDF. The funding effect of INTERREG projects (co-funded by the ERDF) is similar to ERDF projects overall. For the CF, the estimation analysis reveals that there is no significant association between a marginally higher amount of funds received and the change in local economic activity proxied by night light emissions.

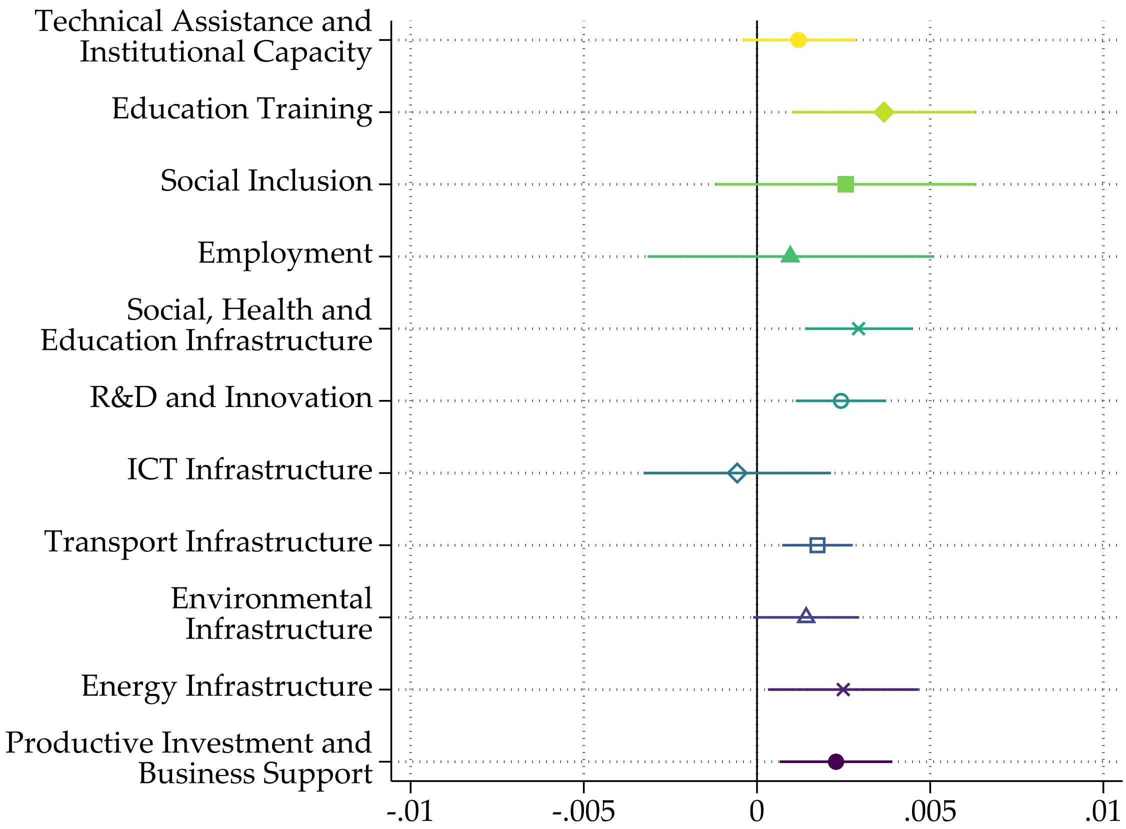


Figure 5 – Funding Effect by Funding Category

Notes: This figure shows for the municipalities under investigation the coefficient estimate and the corresponding 95% confidence band of a regression of the growth in log night light emission in the period 2007-2013 on the total funding amount received as estimated in Column (2) in Table 3, separately for the funding objectives as defined by the European Commission and described in Section 2.

This result holds when excluding Germany as non-CF recipient to avoid a potential sample selection bias, and when differentiating between predominantly rural and other (NUTS-3) regions. The coefficient of ERDF payments remains positive and statistically significant in all specifications.

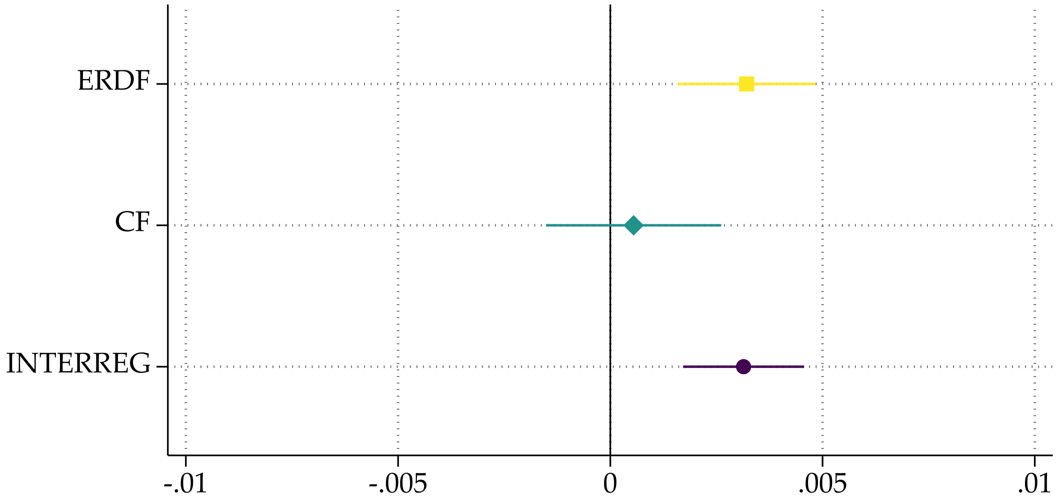


Figure 6 – Funding Effect by Type of Fund

Notes: This figure shows for the municipalities under investigation the coefficient estimate and the corresponding 95% confidence band of a regression of the growth in log night light emission in the period 2007-2013 on the total funding amount received as estimated in Column (2) in Table 3, separately by type of fund.

5 Conclusion and Outlook

This paper has established a novel approach of estimating the effects of EU cohesion policy. For the border area of the Czech Republic, Germany and Poland, official data on projects co-funded by the ERDF and the CF in the programming period 2007-2013 have been standardized, geolocalized and assigned to the smallest administrative unit possible. Combining this database with remote sensing data on night light emission and land cover, we could assess the effect of EU funding on economic growth at the municipality level, where regional GDP data is not available.

We have documented the regional distribution of funds across municipalities in our sample region in terms of thematic categories, funding amounts and the number of projects. Municipalities with a larger population and, on top, an initially higher level of economic activity are more likely to receive a higher amount of EU funding. We then document a positive and statistically significant relationship between EU funding and economic activity as measured by night light emissions. This association becomes stronger when accounting for spillover effects generated by higher funding in neighboring municipalities. Our paper demonstrates that remote sensing data can be effectively used to capture the small-scale economic effects of place-based policies in a pan-European context.

This paper serves as a pilot study which illustrates the potential of our approach for policy analysis. It can be applied in other contexts, for example to study the impact of investment projects funded by Next Generation EU, and rolled out to the entire European

Union. Our research also underlines the added value of better and more timely data for evaluating EU cohesion policy. On the one hand, the availability of project-level data increases transparency and facilitates evaluation studies on the effective use of EU funds. On the other hand, indicators for regional development should be systematically collected also at the municipality level. This would obviate the current necessity to approximate economic growth with nightlight emission data. In addition, future research could consider further variables retrieved from remote sensing data—such as air quality or high-resolution land cover—or other micro-geographic indicators—such as property prices and rents (Ahlfeldt et al., 2022)—to achieve a multidimensional assessment of the effects of EU cohesion policy on the quality of life in Europe's regions.

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A Data Appendix

A.1 Sample Region

Our sample region consists of the municipalities within the NUTS-2 regions Jihozápad (CZ03), Severozápad (CZ04), Severovýychod (CZ05), Střední Morava (CZ07) and Moravskoslezsko (CZ08) in the Czech Republic, Niederbayern (DE22), Oberpfalz (DE23), Oberfranken (DE24), Brandenburg (DE40), Mecklenburg-Vorpommern (DE80), Dresden (DED2) and Chemnitz (DED4) in Germany, as well as Śląskie (PL22), Zachodniopomorskie (PL42), Lubuskie (PL43), Dolnośląskie (PL51) and Opolskie (PL52) in Poland.

As discussed in the Data section, the size of LAU differs across EU member states. Figure A.1 shows the distribution of LAU sizes in the sample region, indicating a relatively high spatial segmentation in the Czech Republic.

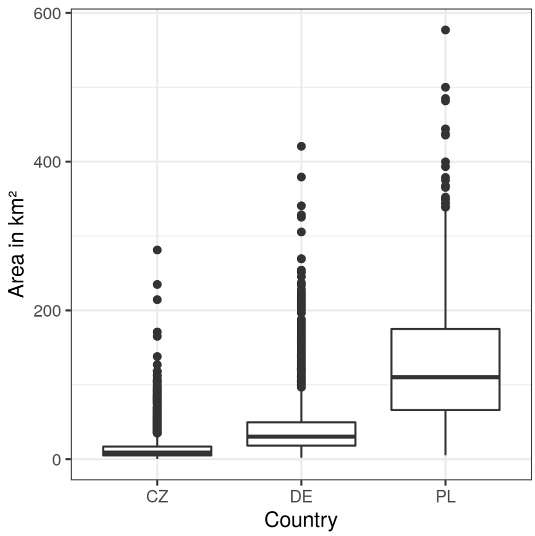

Figure A.1 – Size Distribution of Municipalities per Country in the Sample Region

Notes: The boxplots show the size distribution of all municipalities in the sample region per country (CZ = Czech Republic, DE = Germany, PL = Poland). It is apparent that Poland (the Czech Republic) has the largest (smallest) municipalities with respect to size. Our sample region includes 3,733 municipalities in the Czech Republic, 2,220 municipalities in Germany and 602 municipalities in Poland.

A.2 Remote Sensing Data

Remote sensing data of nightlight emissions used in this paper stem from the "Defense Meteorological Satellite Program Operational Linescan System" (DMSP-OLS). DMSP-OLS data were acquired as uncalibrated yearly stable light composites provided by the

United States National Center for Environmental Information – National Oceanic and Atmospheric Administration (NOAA). To avoid unreasonable conclusions from systematic biases between different yearly composites, inter-calibration is needed. This was conducted following the approach developed by Li et al. (2013) and Wu and Wang (2019). As a baseline, one image is selected against which all the other images of the time series are calibrated. For that we chose the composite of the year 2001 in accordance with previous studies. The inter-calibration involves a five-step process based on the assumption that areas with temporally invariant night light emissions, such as remote forest areas, will show stable emission levels over time. These areas of stable emissions are selected automatically in an iterative process in which overlaying pixels of two yearly DMSP-OLS composites are brought together in a linear regression model. Outliers are then iteratively removed by means of standard deviation of the residuals. This way it is possible to account for systematic bias in the images. This results in a time series of calibrated yearly night light emission mosaics from 1992 to 2013.

Land cover information was acquired in form of yearly land cover data derived from images of the "Moderate Resolution Imaging Spectroradiometer" (MODIS) acqiured by the Terra and Aqua satellites. The MCD12Q1.006 land cover products are accessible free of charge including the IGBP land cover classification (see MODIS User Guide, p. 7). This global product features a set of 17 distinct land cover classes including several types of forests, urban areas or croplands (Friedl et al., 2002). In this study we acquired the entire time series of land cover maps from 2007 to 2013 with a spatial resolution of 500 meters. Since some classes do not appear in the sample region and others are semantically similar, we applied a reclassification scheme to reduce the 17 land cover classes into nine more general classes (cf. Table A.1).

A.3 Data on EU Regional Funds

Our analysis is based on project-level funding data of EU regional funds, collected from websites of regional authorities. In the programming period 2007-2013, for the first time, managing authorities of operational programs designed to implement the EU's cohesion policy were obliged to publish lists of beneficiaries to document the intra-regional distribution of EU regional funds. By regulation (Article 7 of Commission Regulation (EC) No 1828/2006), the minimum content of these lists was the name of the project and the amount of (EU and national) public funding allocated to it. Fortunately, many member states or regions reported project information of greater detail, such as project start and end dates, the location of the project or a thematic categorization of the project.

As there is no central systematic European database providing this data, we collect information from lists of beneficiaries supported by the ERDF and CF from websites of

New classes	IGBP classes
forest	1, 2, 3, 4, 5
grasslands	10
shrublands	6, 7, 8, 9
croplands	12, 14
wetlands	11
urban	13
water	17
snow ice	15
bare soil	16

Table A.1 – Reclassification scheme for IGBP classes

Notes: IGBP classes are (1) evergreen needleleaf forests, (2) evergreen broadleaf forests, (3) decidous needleleaf forests, (4) deciduous broadleaf forests, (5) mixed forests, (6) closed shrublands, (7) open shrublands, (8) woody savannas, (9) savannas, (10) grasslands, (11) permanent wetlands, (12) croplands, (13) urban and built-up lands, (14) cropland / natural vegetation mosaics, (15) permanent snow and ice, (16) barren land, (17) water bodies. Not all IGBP classes are present in the sample region.

national (regional) authorities. Information on INTERREG projects co-funded by the ERDF is downloaded from the KEEP database (https://keep.eu).

To geocode the projects at the municipality level, the data is enriched using geographical information on the project (or beneficiary) reported in lists of beneficiaries. The degree of detail of locational information in lists of beneficiaries differs considerably by country.[15] On the one hand, Czech lists of beneficiaries reported for the programming period 2007-2013 include the municipality in which the projects are carried out, which allows a direct geolocation of projects. On the other hand, Polish lists of beneficiaries report the name of the city (or cities) in which the project takes place, therefore postcodes are assigned using the official list of postal address numbers by the Polish postal service. For Germany, no details on the beneficiary or project location are reported in lists of beneficiaries. Still, the NUTS-1 region in which a project is implemented can be derived from the corresponding operational program. In combination with this NUTS-1 regional information, beneficiary names are then searched for both in the Google Maps application programming interface (API) and the AMADEUS business database by Bureau van Dijk (see https://www.bvdinfo.com/) to learn about its location at the postcode level. If

[15] The sample of projects carried out in the region under consideration is selected based on the NUTS-2 region in which the projects are implemented according to lists of beneficiaries. Due to a lack of data, for Bavaria and Saxony, NUTS-2 regional information could only be derived from the postcode of the beneficiary reported and using correspondence lists provided by Eurostat. Moreover, for 1.5% of Polish projects, no NUTS-2 region of the project but the NUTS-2 region of the beneficiary was reported in the list of beneficiaries, which was then considered for sample selection. For cross-regional INTERREG projects, by design, only the beneficiaries' location is reported (and assumed to be likely to coincide with the project location). Therefore, we consider projects (with lead beneficiaries in the Czech Republic, Germany or Poland) with beneficiaries located in the NUTS-2 regions part of the sample region.

the beneficiary name was found using both sources but with conflicting information, the correct postcode was verified manually by web search and, if possible, a unique postcode was assigned. For INTERREG projects, postcodes of project partners are reported.

As the data is linked to satellite data via the municipality (LAU) code, Czech lists—which include this information—allow for a direct geolocation of projects. For Germany and Poland, we conduct a spatial matching of municipalities (LAU) and corresponding postal codes (zip codes) derived from project data. In this study, spatial locations of the postal codes were acquired from the Geonames project (see www.geonames.org). The points were cleaned of geometric and projection errors. By overlaying the spatial data of both municipality and postal codes, each municipality was assigned with the corresponding postal codes. It is thus possible that a) one municipality comprises multiple postal codes and b) a postal code spans multiple municipalities. In this case, respective project amounts are divided by the number of relevant municipalities. For the analysis of the number of projects, the same project is counted as one in each participating municipality. As a further data cleaning step, information on the correspondence between postal codes and municipality codes from Geonames was verified by checking for the presence of postcodes in official Eurostat lists of correspondence with NUTS-3 regions. Only postal codes included there are considered.

Table A.2 shows the share of the EU funding amount reported in the original lists that could be assigned to a municipality and is therefore considered for the sample of the present analysis (coverage). The fourth column of Table A.2 shows the total EU co-funding amount found for the sample region considered in this paper, and the fifth column compares this amount with official data on regional payments provided by the European Commission's Directorate-General of Regional and Urban Policy (DG REGIO).

While Polish financial project data (commitments) almost fully mirrors official payment data, data on German projects covers around 53% of the payments. This is mainly due to the paucity of detail in the list, which often excludes the full name of the beneficiary firm or fail to give any information on beneficiary or project location. ERDF commitments (as well as planned ERDF payments) reported in the Czech list of beneficiaries for the sample region exceed official payment data, which may be due to overprogramming and deviations in reporting systems.

Country	Fund	Coverage of LAU Information*	Total EU Co-Funding Amount considered	Comparison with EU Payments**
Czech Republic	ERDF	100%	11,801,670,680	118%
Czech Republic	CF	100%	7,569,510,990	111%
Germany	ERDF	62%	3,044,595,710	53%
Poland	ERDF	96%	8,385,492,700	98%
Poland	CF	96%	6,459,921,180	99%
INTERREG	ERDF	88%	644,104,240	n.a.

Table A.2 – EU Co-funding Amounts in the Project Dataset

Source: Lists of beneficiaries published by managing authorities (see https://ec.europa.eu/regional_policy/en/atlas/beneficiaries and KEEP database.
Notes: This table shows EU co-funding amounts (at current prices) that could be assigned to municipalities in the sample region, and the comparison of funding amounts considered in our analysis with official data. In general, the allocated ERDF and CF co-funding amount per project is considered. For projects carried out in the context of operational programs co-funded by both ERDF and CF and for which the relevant type of fund is not reported, the full project amount is split according to the overall co-funding share of each fund in the whole operational program (as reported by DG REGIO). For German projects, only the paid-out sum of both EU and national public co-funding provided for a project is reported. Therefore, we consider as EU co-funding amount the overall share provided by the ERDF among total public funding in the respective operational program according to program information provided by DG REGIO. Germany is not eligible for CF funding. * Share of the total EU co-funding amount allocated (or, for Germany paid out) to projects that could be assigned to a municipality among the total EU funding amount reported in respective source lists of beneficiaries. This check was conducted prior to selecting the sample of regions part of the sample region; for the Czech Republic and Poland there is one national list of beneficiaries, for Germany, lists of beneficiaries for the relevant NUTS-1 regions are considered. **Comparison of total EU co-funding amount in NUTS-2 regions considered (incl. INTERREG) with payments reported for the sample region in the data set of historical regional payments (ERDF and CF, programming period 2007-2013) provided by DG REGIO.

B Additional Figures and Tables

B.1 Night Light Emissions and GDP Growth

	(1) ΔGDP	(2) ΔGDP
ΔNLE	0.170***	0.195***
	(20.83)	(16.57)
Country FE	✓	✓
NUTS-2 FE	-	✓
Observations	6555	6555
R^2	0.198	0.500

Table B.1 – Night Light Emission and GDP Growth at NUTS-3 level

Notes: This table displays the results of two separate regressions of the change in GDP on the change in total night light emission for the period 2007-2013. Robust standard errors, with t-statistics shown in parentheses. Levels of significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.2 Robustness of Baseline Results

To assess the sensitivity of our baseline results with respect to the model specification, we re-estimate Equation 1, but apply the log instead of the IHS transformation. We thereby drop all municipalities which received no funding at all and only consider the intensive margin of the funding effect. Table B.2 shows that the estimated coefficients approximately double. We also repeat this analysis without any transformation of the funding amount and estimate a log-level model. Results do not change much (results available upon request).

	(1)	(2)	(3)	(4)
	ΔNLE	ΔNLE	ΔNLE	ΔNLE
Funding Amount	0.0165***	0.00754**	0.0165***	0.00765**
	(4.32)	(2.70)	(4.19)	(2.73)
$\log(NLE_{2007})$	-0.0708***	-0.169***	-0.0726***	-0.170***
	(-4.21)	(-5.68)	(-4.27)	(-5.68)
Share Urban$_{2007}$		-0.259***		-0.255***
		(-6.16)		(-5.62)
Share Cropland$_{2007}$		-0.128***		-0.133***
		(-4.67)		(-4.51)
log(Population)		0.111***		0.111***
		(5.89)		(5.89)
NUTS-2 FE	✓	✓	-	-
NUTS-3 FE	-	-	✓	✓
Observations	5692	5692	5692	5692

Table B.2 – Results for the Log of Funding

Notes: This table reports the estimates of a regression of the growth in log night light emission in the period 2007-2013 on the total funding amount received by each municipality and controls. Other than in Table 3, we apply the log transformation instead of the IHS transformation to the funding amount. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.3 Effect of Number of Projects

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
Number of Projects	0.000171**	0.0000849*	0.000287**	0.000157***
	(2.74)	(2.55)	(2.71)	(3.75)
$\log(NLE_{2007})$	-0.0558***	-0.179***	-0.0595***	-0.183***
	(-3.86)	(-5.87)	(-4.07)	(-5.89)
Share Urban_{2007}		-0.292***		-0.290***
		(-5.92)		(-5.58)
Share Cropland_{2007}		-0.131***		-0.138***
		(-5.11)		(-5.07)
log(Population)		0.129***		0.129***
		(6.11)		(6.04)
NUTS-2 FE	✓	✓	-	-
NUTS-3 FE	-	-	✓	✓
Observations	6555	6555	6555	6555

Table B.3 – Night Light Growth and Number of Projects

Notes: This table reports the estimates of a regression of the growth in log night light emission in the period 2007-2013 on the total number of projects funded in each municipality and controls. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.