Regional Science and Urban Economics 103 (2023) 103954

Contents lists available at ScienceDirect

Regional Science and Urban Economics

journal homepage: www.elsevier.com/locate/regec

EU cohesion policy on the ground: Analyzing small-scale effects using satellite data[☆]

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ARTICLE INFO

JEL classification:
R11
O18
H54

Keywords:
Regional development
EU cohesion policy
Remote Sensing

ABSTRACT

We present a novel approach to analyze 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 receiving 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 comprehensive cross-border data are not available at such a spatially granular level.

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 in the EU budget. However, despite its financial relevance, there exists no clear consensus in the literature on the effectiveness of EU cohesion policy in promoting economic development. One reason for the lack of clear empirical evidence is that data on EU funding are 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 of 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 to 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 exploit 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 aggregated municipality-level total 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 the municipalities located in the NUTS-2 regions adjacent to the border between the Czech Republic, Germany, and Poland for the programming period 2007–2013. Given the considerable effort required both to process the satellite data and to geocode cohesion policy funding at the municipality level, our analysis is based on the above subsample of EU regions for three reasons: the availability of the information required to geocode the funding data, the availability of high-resolution satellite imagery for a long period

☆ We are grateful to the editor (Gabriel Ahlfeldt), two anonymous referees, as well as Katharina Gnath, Natascha Hainbach, Peter Mayerhofer, and conference participants at the University of Regensburg (VfS) for helpful comments and suggestions. The results and their interpretation are solely the authors' responsibility. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. We gratefully acknowledge financial support from the Bertelsmann Foundation. Elisabeth Arnold, Peter Reschenhofer, Maria Riegler, Theresa Schröter, Jelena Todorovic, and Diego Alonso Alarcón Díaz provided excellent research assistance.

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https://doi.org/10.1016/j.regsciurbeco.2023.103954
Received 25 October 2022; Received in revised form 26 September 2023; Accepted 29 September 2023
Available online 4 October 2023

of time, and the large variation in EU funding activity across municipalities. Considering regional (e.g. level of economic development) and local (e.g. population size of municipalities) characteristics, our analysis not only distinguishes between different funding categories, but also separately estimates the effects of projects co-funded under inter-regional (INTERREG) programs (such as Bavaria–Czech Republic or Czech Republic–Poland).

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. As we observe more than 6500 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 the level of economic development and the receipt of EU funding, which arises because NUTS-2 regions with a GDP per capita of less than 75% of the EU average are eligible for the convergence objective and receive more funding. Furthermore, we establish stylized facts on the distribution of EU regional funds and document the relationship between economic activity and EU funding by funding objective.

As an illustrative example, Fig. 1 shows Katowice Airport in 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 works in 2007 and 2013, respectively. Further infrastructure development can also be seen around the airport, 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 the area in 2007 and 2013 (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.

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. Holding 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 may reflect agglomeration effects and the role of favorable ecosystems (in cities) in attracting more EU funds.

Second, we describe systematic differences in the quantity and types of funding across countries. For example, municipalities in Poland implemented much larger individual projects than municipalities in Germany or the Czech Republic during the programming period under consideration (2007–2013). 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 such as roads or railways, which constitutes a particularly costly type of project.

Third, municipalities that received more EU funding experienced a significantly stronger increase in night light emissions during the programming period. The association between funding and growth in night light emissions is stronger when spillover effects from neighboring municipalities are taken into account. While our analysis, like much of the prior literature, cannot rule out all confounding factors and therefore may not provide 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 that 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, reflecting 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 a region's human capital endowment (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 take into account the wide 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 that 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) examine the effect of EU cohesion policy on Italian regions using project-level data at the municipality level, with conclusions drawn for a less granular regional level.[2]

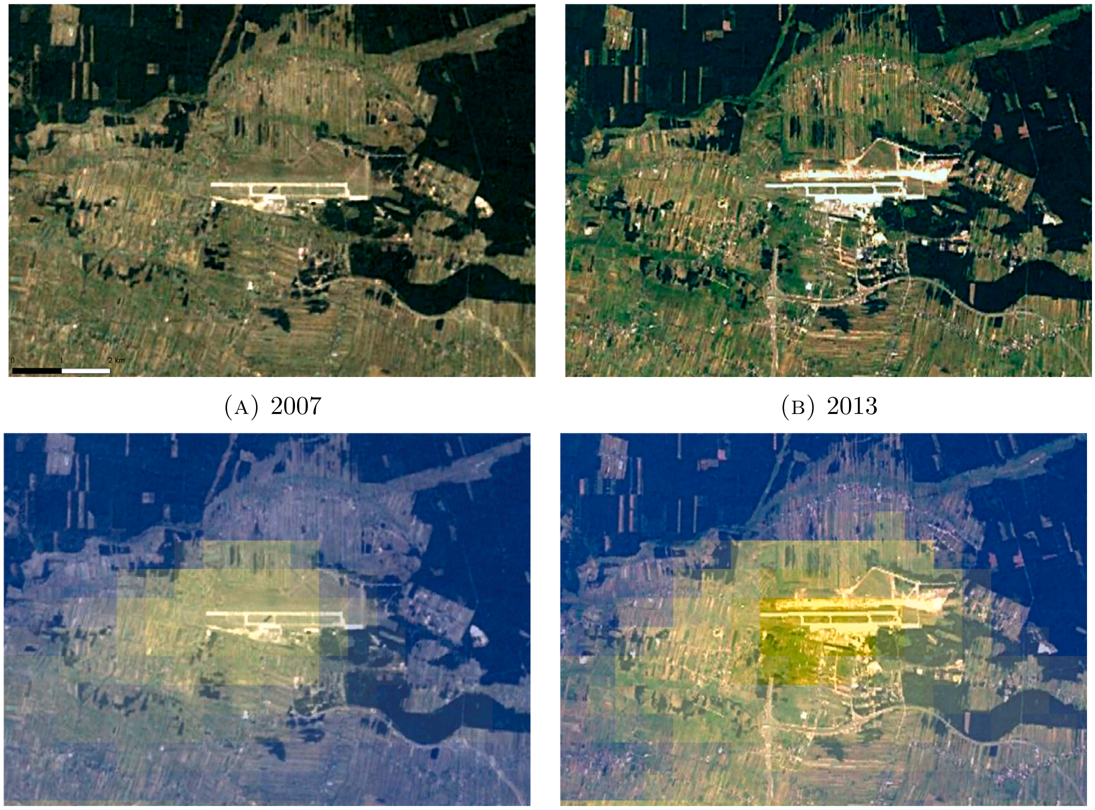
We conduct a more fine-grained analysis of cohesion policy spending, namely at the sub-regional level of municipalities across several countries. Our results show that not only (NUTS-2) regional but also local characteristics as well as the type of projects selected for implementation in a municipality matter for policy effects. This intra-regional perspective has been neglected in most previous research. Thus, our study contributes to a better understanding of the differential regional policy effectiveness. In addition, we differentiate between permanent versus transitory effects and show that a substantial part of the funding effect is still present after construction is finished. Our fine-grained analysis also enables us to test for local spillovers, detecting positive spillovers to surrounding municipalities.

Second, our paper relates to a growing literature documenting 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. Hu and Yao, 2022; Jean et al., 2016; Mellander et al., 2015), as in this study.[3] For example, 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 measurement error (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.

[1] Rodríguez-Pose and Fratesi (2004) point to different impacts of types of policy actions on economic growth. Mohl and Hagen (2010) distinguish 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 previous 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 kind of data gap: While in Europe information on GDP and other central indicators is available down to the NUTS-3 level, there is no (cross-border) information available at the more granular level of municipalities. Moreover, granular national accounts data are only released with a significant time lag of several years. Accessing real time satellite imagery therefore also provides an advantage for policy analysis.



(A) 2007 (B) 2013

(C) 2007 (D) 2013

Fig. 1. EU-funded Expansion and Modernization of Katowice Airport, 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.

The remainder of the 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 the growth of night light emissions. Section 5 summarizes our findings and discusses how our insights may prove valuable for future research.

2. Institutional setting and data

2.1. Institutional setting

EU cohesion policy aims to reduce economic and social disparities between 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 by beneficiaries such as 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 of less than 75% of the EU average over a three-year period prior to the programming period—under the so-called Convergence Objective. The remaining ERDF (and ESF) budget in the 2007–2013 period is allocated under the objective of regional competitiveness and employment, and territorial cooperation (through INTERREG(ional) programs). Only EU member states with a gross national income below 90% of the EU average are eligible for CF funding, which means that Germany is not a recipient country of CF funds.

In the first step, the national strategic reference framework, designed by the member states and endorsed by the European Commission, defines the priorities and objectives 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. All three countries in our sample region both implement cohesion policy through operational programs for specific regions (NUTS-2 regions in the Czech Republic and Poland, NUTS-1 regions in Germany) as well as national programs (such as Technical Assistance, Innovative Economy, Infrastructure and Environment). While the distribution of funding available to a regional program across thematic priority areas is agreed on between the regions, member states and the European Commission, there is no regulation or general rule for the distribution of funding to different districts or municipalities. Often, the respective regional or national managing authorities issue calls for project proposals and define project selection criteria on which funding decisions for specific projects shall be based. Beneficiaries can then apply with their proposed projects for co-financing. Administrative capacity for promoting funding opportunities and providing support for project proposals may help to attract funds to municipalities within a certain region or district. Moreover, while funding for infrastructure development spreads across many municipalities, cities or municipalities with a pre-existing industrial center are likely to attract more funds for, for example, research and innovation activities or productive investment.

Since the 2007–2013 programming period, information on these projects and their corresponding beneficiaries has to be made publicly

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

available by the managing authorities. As there is no official and unique database containing project-level information provided by the 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 the municipalities and communes of the European Union.

Substantial data efforts are required both for processing the satellite data used in the analysis and for geocoding the cohesion policy funding on the municipality level. We therefore choose a subsample of regions and select a sample spanning more than one country to test for the feasibility of the approach—ranging from the geocoding of projects, preparing the satellite data, combining the datasets at the LAU level, and performing the analyses (considering different LAU sizes in different countries, etc.)—in a pilot study setting. For the Czech Republic, Poland and several regions in Germany, the coverage of information required for the geocoding of funding is relatively high, and satellite imagery is available for a long period of time.

Against this background, we collect data for the NUTS-2 regions adjacent to the border 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, such as 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. Fig. 2 depicts the sample region. While the investigated region comprises 17 NUTS-2 regions and 102 NUTS-3 regions, it consists of 6555 municipalities.[5]

Data on EU funding. As the policy variable of interest, we explore EU support provided via the ERDF and CF. Projects co-financed by the ESF are not considered in the baseline results, as information on the exact location of a large share of final beneficiaries (often individuals) is not 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 inter-regional 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, the ERDF increasingly focuses on supporting research and innovation as well as increasing the competitiveness of small and medium-sized enterprises. Fig. 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 addresses this category, as well as 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 targets 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 to aggregated official numbers. If the project location is not reported by the managing authorities, we use the headquarters 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 and economic activity. 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 emissions have been associated with urban and regional economic development in previous studies (Zhu et al., 2017; Wu and Wang, 2019). 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 under an 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. The DMSP data encodes each pixel of a resolution of 30 arc-seconds with digital numbers (DN), which measure annual brightness on a relative scale ranging from 0 to 63. Our main analysis focuses on the growth in total night light emissions, i.e., the sum of digital numbers, per LAU.[9]

More specifically, we use DMSP-v4 yearly stable lights composites (Baugh et al., 2010). These have the benefit of minimizing the influence from atmospheric or extraterrestrial light. In Appendix A.2, we describe the preprocessing steps applied to the raw data. One drawback of DMSP Data in comparison to the latest generation of sensors, e.g. VIIRS, is the phenomenon of blurring, which was previously discussed, e.g., in the context of urban studies (Small et al., 2005; Abrahams et al., 2018; Zheng et al., 2020). We address this in more detail in Section 4.4.

[5] From initially 6571 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. Fig. 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 3733 municipalities in the Czech Republic, 2220 German and 602 Polish municipalities. Berlin, Germany, is excluded because it is not a NUTS-2 region bordering any of the countries. Due to Berlin's unique status being simultaneously a NUTS-2, NUTS-3, and LAU area, including Berlin in estimations with NUTS-2 or NUTS-3 fixed effects would not change our results.

[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.

[9] This measure of aggregate, rather than average, night light emissions was chosen as we aim to proxy for overall economic activity in a given LAU when analyzing the distribution of funds. As we focus on growth rates in night light emissions when relating them to funding received, this approach is, however, equivalent to assessing the growth in average night light emissions, or night light intensity, which is frequently used in the economic literature.

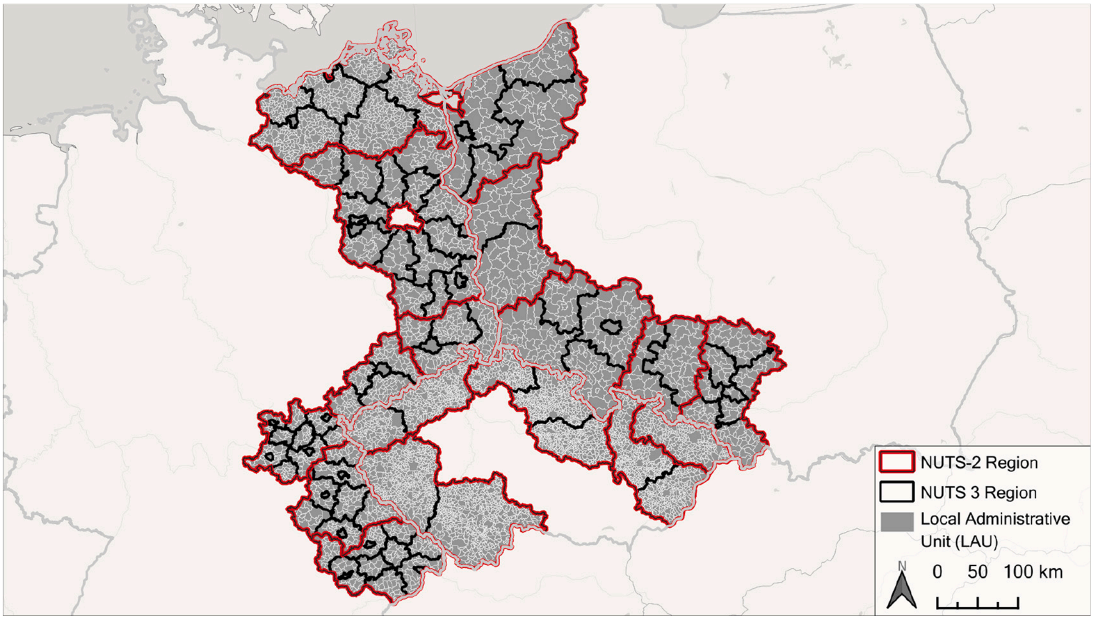


Fig. 2. Overview of the Sample Region.
Notes: This figure shows NUTS-2 and NUTS-3 regions as well as Local Administrative Units in the border region between the Czech Republic, Germany and Poland. The sample region comprises the municipalities located in the NUTS-2 regions adjacent to the border, which is why the NUTS-2 region of Berlin (corresponding to one NUTS-3 region and one LAU) is not included. We exclude 16 uninhabited military training grounds with own municipal status in Germany and the Czech Republic.

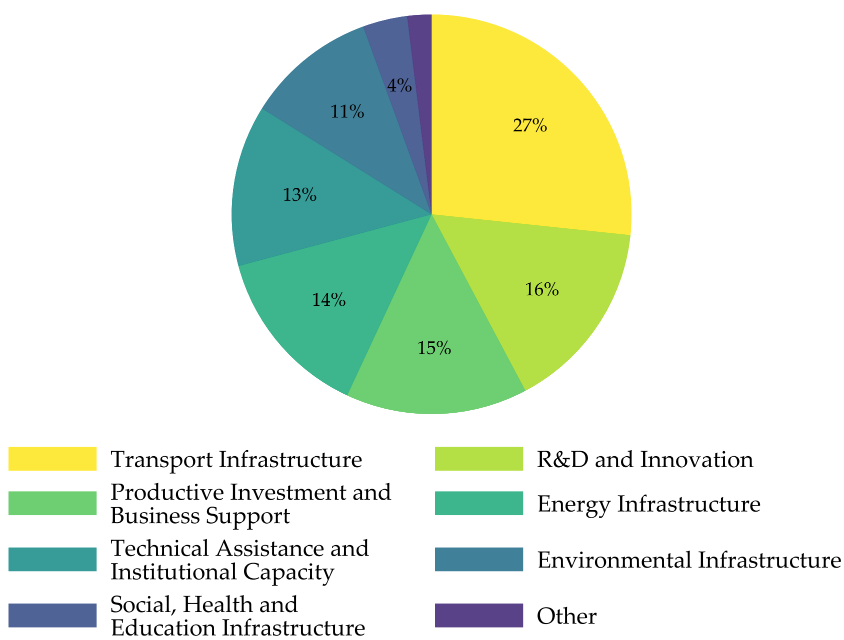


Fig. 3. Distribution of ERDF and CF Co-funding by Thematic Categories.
Notes: This figure shows the distribution of ERDF and CF co-funding in the sample region by broad funding categories. See Table A.2 in the Appendix for details on overall funding amounts.

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. Through this spatial aggregation, we assume the impact of DMSP's blurring effect to be constant throughout the study region.

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, an increase in night light emissions' growth by 1 percentage point was associated with an increase in GDP growth by 0.170 percentage points, which rises to 0.195 percentage points when accounting for NUTS-2 fixed effects. Our

Table 1
Summary statistics by municipality.

	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%

Notes: This table displays summary statistics for the number of projects, the funding amount (in 1,000 Euro), the aggregated total night light emission per municipality and the growth of night light emission per municipality. All statistics refer to the whole funding period 2007–2013. Night light emissions per pixel of a resolution of 30 arc-seconds are registered as digital numbers (DN, 0 to 63) by the DMSP-OLS sensor. We calculate total municipal night light emissions as the sum of the registered night light emissions per municipality.

estimates are consistent with prior literature (Henderson et al., 2012; Lessmann and Seidel, 2017), which indicates that growth in night light emissions is a good proxy for GDP growth 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.

3. Spatial distribution of EU regional funds

The dataset 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 dataset allows us to differentiate between thematic categories, and to document which municipalities in our sample region invested how much of EU funding in which area.

Fig. 4 maps the intensity of EU funding received in the 2007–2013 programming period in terms of the number of projects and the sum of committed EU funding per municipality in current prices.[10] The total number of projects implemented in a municipality in the sample region ranges from 0 to 3189 (Table 1). The distribution of projects across municipalities is skewed: The average number of projects per municipality amounts to 17, while half of the municipalities carried out three or fewer projects. The highest number of projects in our sample is documented for the German cities of Dresden and Chemnitz, which can be explained in parts by an agglomeration of economic actors that apply for relatively large (research and innovation or productive investment) projects. In small municipalities in rural areas, the presence of few (or no) firms also contributes to a lower number of projects co-funded by the ERDF or CF.

The average funding amount per project in a municipality in our sample amounts to 261,190 Euro. As Panel (B) of Fig. 4 shows, there is a large dispersion of funding amounts between and within countries. One factor is that Germany receives no funding from the Cohesion Fund and, by definition, less from the ERDF due to the level of development of its NUTS 2 regions in the sample.

Moreover, while the average funding amount per project is 112,670 Euro in the German municipalities and 295,480 Euro in the Czech municipalities, it is considerably 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, where large amounts are allocated to transportation and environmental infrastructure. Additional factors influencing the individual projects' volume could be the size or industry of beneficiaries (Bachtrögler et al., 2019), but also different project selection or reporting schemes across countries or regions (e.g., allocation of funds for one infrastructure project to one provider or in tranches to more than one beneficiary).[11]

When analyzing the absolute amounts of funding received, it is necessary to take into account the different sizes of municipalities across countries, as they are significantly larger in terms of area and population in Poland than in Germany and—particularly—in the Czech Republic.[12] The three municipalities receiving 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 that explores 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 emissions) or strong (high level of night light emissions) municipalities. Moreover, we add the population of 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 include 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.

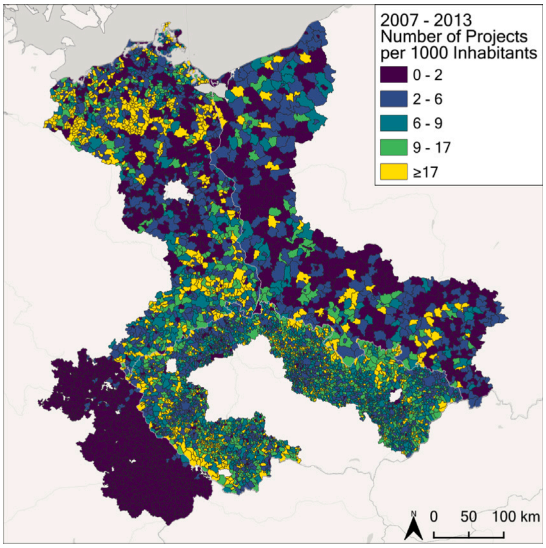
The result of this analysis suggests that the sum of ERDF and CF funds allocated to municipalities is directly linked to the initial level of economic activity, measured in terms of the sum of night light emissions in 2007. This finding indicates that, within our sample region, higher amounts of funding are allocated to municipalities with a relatively high level of economic activity prior to receiving funding. 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—to be an important determinant of the funding amount received. In addition, funding amounts are lower in municipalities with a higher share of cropland.[13]

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

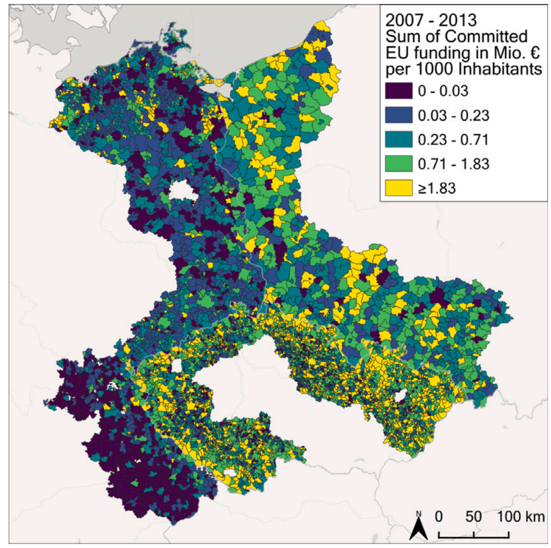
[11] Bachtrögler et al. (2019) conduct an EU-wide analysis of cohesion policy projects in the 2007–2013 programming period, which explores regional, project and beneficiary characteristics that determine an individual project's total value. First, projects are found to be on average significantly larger in less developed regions. Second, the paper finds that ERDF- and CF-funded projects are larger in terms of funding than ESF-funded projects, and that 'Road, Rail and Other transport' projects are allocated the highest funding amounts. Third, larger beneficiary companies seem to carry out larger projects. Finally, the paper also finds that remaining unexplained variation in individual project volumes differs systematically across member states, which may be due to different implementation and/or reporting schemes.

[12] Note that while there are non-negligible differences in average funding amounts and project types across countries, which are partly due to different national features and levels of development, our later estimations control for NUTS-2 or NUTS-3 fixed effects. That is, we compare the differential effects of EU funding within a given region. Therefore, the results in Section 4 are neither driven by different national features nor by differences in the level of development between NUTS-2 or NUTS-3 regions, but rather by variation in funding at the local level.

[13] Controlling for municipality population yields a very similar coefficient for the association between initial night light emissions and funding per capita rather than overall funding (results available on request).



(A) Number of Projects



(B) Sum of Committed Funding

Fig. 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 sample region comprises the municipalities located in the NUTS-2 regions adjacent to the border, which is why the NUTS-2 region of Berlin (corresponding to one NUTS-3 region and one LAU) is not included. 16 LAUs without population are excluded, e.g., military areas or areas without local authority. The colors represent quintiles of the distribution of the respective variable.

Table 2
Relationship between EU funding and night light emissions.

	(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

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: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

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. 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 lower economic activity. For the CF, the result appears less intuitive, as it mainly supports infrastructure projects, which could also be located in rural areas. Indeed, separate regressions for ERDF and CF funding intensity confirm that there is no statistically significant link between initial economic activity and CF funding 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 allocate funds randomly across municipalities or regions, so that the funding effect is independent of any other factors accounting for growth rate differentials. In reality, most of the funds are instead explicitly targeted at economically less-developed NUTS-2 regions.[14] The main strength of our research design is the ability to observe variation in EU funding *within* NUTS-2 and NUTS-3 regions. This allows us to break the mechanical endogeneity of funding and economic growth (proxied by growth in night light emissions) by including fixed effects at the level of NUTS-3 regions. In all of our analysis, we thus compare whether municipalities within a given NUTS-3 region that received comparatively more funding experienced stronger growth.

However, even within a given NUTS-3 region, it is likely that the EU funding amount committed to a municipality depends on observable and unobservable local characteristics, such as the presence of innovative actors who 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 population size and land cover. To account for these factors as well as for a potential convergence effect (municipalities with a higher level of initial night light emissions grow at slower rates), 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.[15] 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-3 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-3 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

[14] Becker et al. (2010) have exploited the cut-off point of regional GDP per capita being 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.

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

night light emissions 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 this sense, our results answer the question whether municipalities that received more funding grew more strongly—and not necessarily to what extent the funding *induced* them to grow more strongly.

In our analysis, funding is mainly measured in terms of the total amount of funding a municipality received over the funding period. To assess the effect of percentage increases in funding amounts, our baseline estimates employ an inverse hyperbolic sine transformation.[16] As a robustness check, we also use the logarithm of the funding amount (dropping municipalities that 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.[17]

Table 3
Night light growth and funding amounts.

	(1) ΔNLE	(2) ΔNLE
Funding Amount	0.00745***	0.00334**
	(4.38)	(3.03)
log(NLE_{2007})	−0.0694***	−0.184***
	(−4.46)	(−5.89)
Share Urban$_{2007}$		−0.278***
		(−5.49)
Share Cropland$_{2007}$		−0.136***
		(−5.08)
log(Population)		0.126***
		(5.95)
NUTS-3 FE	✓	✓
Observations	6555	6555

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-3 fixed effects. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

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 use NUTS-3 fixed effects. Hence, we compare how the growth rate of night light emissions varies at the municipality level within a given (less developed or high-income) NUTS-3 region as a reaction to the funding received, holding initial night light emissions fixed. Our estimations yield a coefficient of 0.00745, meaning that a 1% increase in EU funding is ceteris paribus associated with a 0.007 percentage points higher growth rate in night light emissions. This estimate barely changes when employing fixed effects at the broader level of NUTS-2 regions (see Appendix Table B.2).[18]

In Column (2) of Table 3, where we estimate the most comprehensive model additionally controlling for log population and the respective proportions of urban area and cropland at the start of the funding period, the funding coefficient is estimated at 0.00334.[19] For the average municipality within our sample region, which receives annual funding worth 625,500 Euro, we thus find that total night light emissions increase by 0.05%.

Our results also indicate that—controlling for the development status of the specific region—growth in night light emissions is smaller in municipalities with higher initial night light emissions, which proves to be a robust result in all model specifications. This points to an economic convergence effect, which may, however, be partly attributable to higher income municipalities investing more in e.g., scientific and technological innovation, which may be less reflected in night light emissions (see, e.g., Hu and Yao, 2022). Still, note that our fixed effects estimations contrast municipalities within the same, similarly developed region, attenuating possible biases. Also, note that through DMSP's blurring effect and through spatial spillovers, one municipality's increase in night light emissions could in part be affected by neighboring municipalities. A misattribution of night lights to municipalities at the local level could possibly lead to biased estimates. We address these issues in Section 4.4.

What does the estimated effect of funding on night light emissions 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/night light 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%.

4.3. Robustness checks

Alternative specifications. Our baseline specification uses the inverse hyperbolic sine transformation to capture the effect of a percentage increase in funding. We use numerous alternative specifications as robustness checks. First, Appendix Table B.3 (Columns (1) and (2)) reports significantly positive effects when using the untransformed funding amount in million Euros instead. Second, 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

[16] 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 to 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. Very similar results are obtained when using $ln(1 + x)$ instead (available on request).

[17] Our approach to clustering follows the thought that one should cluster standard errors at the level of treatment variation. Because treatment intensity differs systematically at the level of NUTS-2 regions, due to the EU regulations that NUTS-2 regions below the 75% GDP threshold receive more funding, one would like to cluster standard errors at the NUTS-2 level. However, this leads to an overly low number of just 17 clusters, which may lead to a downward bias in standard errors (Cameron et al., 2008). We therefore decided to cluster at the level of NUTS-3 regions (102 clusters), which are nested within NUTS-2 regions. Note that this is a conservative approach, as the clustered standard errors are larger than those one would obtain using robust standard errors only.

[18] 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 estimate a specification with NUTS-2 fixed effects and show in Appendix Table B.2 that the choice of the level for the fixed effects does not affect our results. Moreover, our results are robust to excluding NUTS-3 regions one-by-one (see Appendix Fig. B.1), suggesting that our findings capture overall effects that are not primarily driven by individual regions.

[19] While our main analysis focuses on the ERDF and the Cohesion Fund, comparable results emerge when including the subset of ESF funded projects that is geocoded at the municipality level (results including ESF funding in 132 Czech municipalities are available upon request).

Table 4
Spillover effects from funding in neighboring municipalities.

	(1) ΔNLE	(2) ΔNLE
Funding Amount	0.00696***	0.00290**
	(4.50)	(2.80)
Funding Amount in Neighboring Municipalities	0.00371	0.00433*
	(1.68)	(2.37)
Funding Amount Neighbors of Neighbors	0.00575*	0.00368*
	(2.23)	(1.99)
$\log(NLE_{2007})$	−0.0738***	−0.189***
	(−4.49)	(−5.91)
Share Urban$_{2007}$		−0.279***
		(−5.67)
Share Cropland$_{2007}$		−0.133***
		(−5.17)
log(Population)		0.126***
		(5.92)
NUTS-3 FE	✓	✓
Observations	6551	6551
H0: Joint Effect>0, p-value	0.0036	0.0044

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 variables *funding amount in neighboring municipalities* and *funding amount neighbors of neighbors* are computed as the sum of funding received by, respectively, all directly adjacent municipalities and all neighbors of adjacent municipalities (and transformed using the IHS) and indicate the size of spillover effects. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

the main regressor instead of the total funding amount (Appendix Table B.3, Columns (3) and (4)). Third, our results are robust to splitting funding of joint projects to municipalities based on population weights (Appendix Table B.4, Columns (1) and (2)). Fourth, we test for effects at the intensive margin by limiting the sample to municipalities that attain funding by using the log transformation instead. Estimates approximately double when only considering the intensive margin (see Appendix Table B.4, Columns (3) and (4)).

Assessing pre-trends and selection effects. Our findings are not merely driven by pre-trends or selection effects. As shown in Appendix Fig. B.2, municipalities with above median funding in 2007–2013 did not exhibit notably higher growth rates prior to 2007. After 2007, municipalities with above median funding grew more strongly than municipalities with below median funding, consistent with our baseline results. Similarly, a placebo exercise on the preceding funding period shows no predictive power of the amount of funding a municipality received in 2007–2013 for the growth in NLE in the seven prior years from 2000–2006, before municipalities received funding (Appendix Table B.5). A further robustness check confirms that our baseline estimates barely change when controlling for lagged growth in NLE (Appendix Table B.6).

Distinguishing between temporary and permanent effects. Our baseline results may be driven by two distinct factors: Temporary, light-intensive construction activity without any long-run impact on economic activity, and permanently increased economic activity resulting from the funding project. With the latter as a primary outcome of interest for policymakers, assessing the effectiveness of funding for local economic activity requires distinguishing both factors.

We employ two approaches to discriminate between temporary and permanent effects. First, we directly exploit project end dates, which we observe for a subset of our sample (92% of all projects). For about 58% of those projects, the project (e.g., construction) was finished prior to 2013. We hence estimate effects between 2007 and 2013 for (i) the subset of projects that ended prior to 2013 and (ii) the subset of projects that were still ongoing in 2013. As shown in Appendix Table B.7 (Columns (1) to (4)), comparable results emerge for both subsets, pointing to a persistent positive funding effect on economic activity. The smaller effects compared to our baseline (Table 3) may be driven by the smaller number of projects and the omission of projects without a clearly defined end date.

Second, to mitigate such sample selection effects, we analyze effects for all projects that received funding in the first half of the MFF in 2007–2009, assuming that despite possible delays, construction activities were finalized prior to 2013. As shown in Appendix Table B.7 (Columns (5) and (6)), the magnitude of coefficients is only slightly below our baseline estimates, again highlighting the persistence of effects. Setting the funding amount coefficient reported in Column (6) in relation to our baseline estimate (Column (2) of Table 3), one could infer that 90% of the total funding effect is a permanent effect. However, this estimate should be taken with a grain of salt and viewed as an upper bound for the permanent effect, as we cannot rule out that construction activity of projects that started early in the MFF was completed in 2013. Moreover, the estimated coefficients in Table B.7 (Columns (5) and (6)) may be upward biased by the omission of projects that were funded later during the MFF.

4.4. 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. This effect may be twofold: higher funding in one municipality might affect not only local growth in night light emissions but also in neighboring municipalities. The effects on neighboring municipalities could theoretically be positive or negative. In the example of Katowice in the introduction, the airport expansion appears to have brought substantial economic benefits for Katowice itself. In addition, 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 reduce commuting times for inhabitants of neighboring municipalities, possibly attracting further economic activity to these municipalities. Such spillover effects do not always have to be positive, though: 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.

To test for such spillover effects, Table 4 re-estimates our baseline specification, but additionally controls for the funds flowing into neighboring municipalities. To do so, we first 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. Second, DSMP-OLS data suffers from spatial blurring, i.e., a smearing of light emissions in space at a local level. As measurements for immediate neighbors may be affected by such spatial blurring, and to capture spillover effects at a broader geographic scale, we include a second variable measuring funding received by neighbors of neighbors, i.e., by municipalities that are not directly adjacent to the respective municipality.[20] Coefficients on both variables are positive, albeit only borderline significant. This indicates that spillover effects are present and on average positive. The joint effect is

[20] DSMP-OLS data suffers from spatial blurring, i.e., a 2D Gaussian blur with $\sigma = 1.55$ km resulting from data collection issues and geolocation errors (Abrahams et al., 2018). That is, 99% of the blurring is to be expected in an area with radius 4.65 km around a point-shaped light source. Hence, effects on neighbors of neighbors should not be affected by blurring. An alternative approach in Appendix Table B.8 addresses blurring by measuring night light emissions only in the core settlement areas of municipalities and neighboring municipalities.

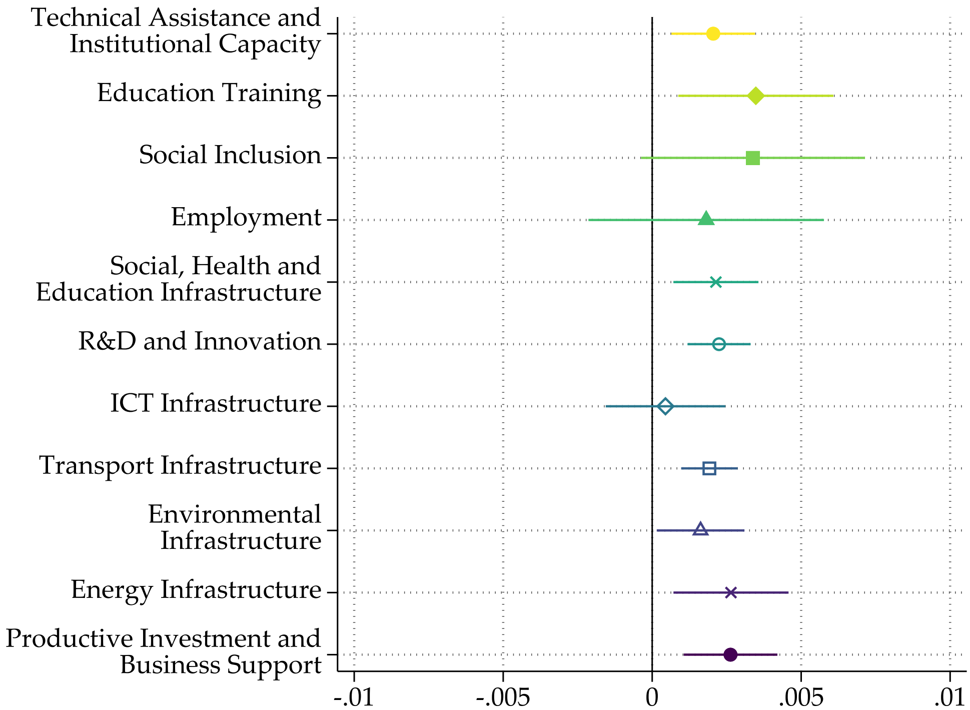


Fig. 5. Funding Effect by Funding Category.
Notes: This figure shows for the municipalities under investigation the coefficient estimate and the corresponding 95% confidence interval of a regression of the growth in log night light emission in the period 2007–2013 on the total funding amount received as estimated in the specification shown in Column (2) of Table 3, separately for the funding objectives as defined by the European Commission and described in Section 2.

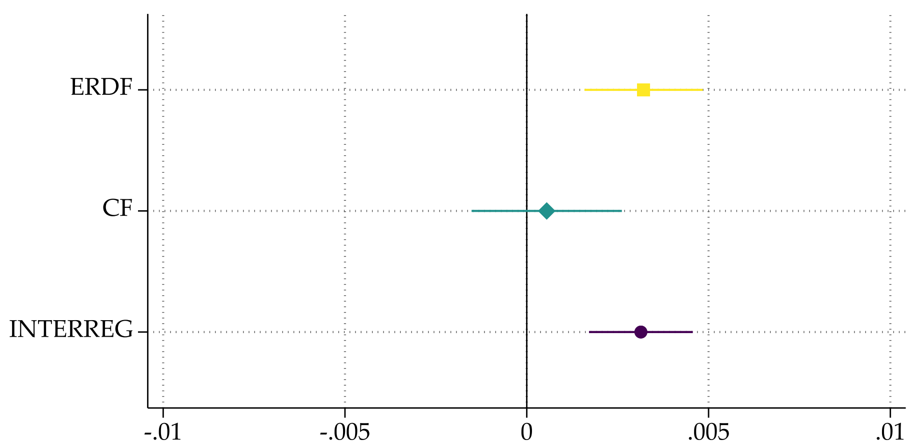


Fig. 6. Funding Effect by Type of Fund.
Notes: This figure shows for the municipalities under investigation the coefficient estimate and the corresponding 95% confidence interval of a regression of the growth in log night light emission in the period 2007–2013 on the total funding amount received as estimated in the specification shown in Column (2) of Table 3, separately by type of fund. While we cannot reject that the effect of ERDF and INTERREG funding is the same (p = 0.559), the effect sizes of both ERDF and INTERREG are significantly larger than the effect size of CF funding (p = 0.013, p = 0.001).

significantly positive (see the bottom line of Table 4). If these variables fully captured the spillover effect, the total funding effect would be the sum of all three coefficients. For example, the total funding effect in Column (2) of Table 4 is 0.00290+0.00433+0.00368=0.01091, as compared to an estimate of 0.00334 in Column (2) of Table 3. This indicates that the estimates in Table 3, which capture the treatment effect on the respective municipality, structurally underestimate the total treatment effect on the overall region.

4.5. Heterogeneity

A key feature of our dataset is the ability to differentiate between types of funds and between funding objectives. In what follows, we present a heterogeneity analysis of the relationship between different types of funding and growth in local economic activity.

Heterogeneity by funding categories. As described above, remote sensing data may differ in their ability to capture the impact of different projects, depending on the category of funding. 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 aimed at promoting education or social cohesion. Fig. 5 shows that the funding effect indeed varies by project category. For the categories *ICT Infrastructure*, *Employment*, and *Social Inclusion*, the funding effect is insignificant. In contrast, there is a significantly positive relationship between the change in local economic activity and EU funding in categories such as *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. 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 be an indication of further private investment following the initial funding.

Heterogeneity by type of fund. Furthermore, we compare the funding effect by the type of fund, keeping in mind that the German municipalities do not receive CF funding by design. As in our baseline specification presented in Table 3, we control for the number of inhabitants, land cover and initial night light emissions, but now run three separate regressions considering the specific amounts per type of fund. Fig. 6 shows that funding effects are significant for projects co-funded by the ERDF. The funding effect of INTERREG projects (co-funded by the ERDF) is similar to ERDF projects. For the CF, we do not find a significant funding effect.[21] This result holds when excluding Germany as a non-CF beneficiary to avoid a potential sample selection bias, and when distinguishing between predominantly rural and other NUTS-3 regions. The effect of ERDF funding remains positive and statistically significant in all specifications.

5. Conclusion and outlook

This paper has established a novel approach to 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 were standardized, geo-located, and assigned to the smallest administrative unit possible. Combining this database with remote sensing data on night light emission and land cover, we assess the effect of EU funding on economic growth at the municipal level, where regional GDP data are 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 a higher initial 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 EU 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. Analyses like these will greatly benefit from and increase in accuracy with higher quality and better-resolved night light satellite data, e.g., from the VIIRS sensors.

This paper serves as a pilot study illustrating the potential of our approach to 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 across 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 need to approximate economic growth with night light emission data. In addition, future research could consider further variables derived 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., 2023)—to achieve a multidimensional assessment of the impact of EU cohesion policy on the quality of life in Europe's regions.

[21] Appendix Table B.9 separately reports the underlying estimates for ERDF, Cohesion Fund, and INTERREG projects.

CRediT authorship contribution statement

Julia Bachtrögler-Unger: Conceptualization, Methodology, Formal analysis, Writing, Funding acquisition. **Mathias Dolls:** Conceptualization, Methodology, Writing, Funding acquisition. **Carla Krolage:** Conceptualization, Methodology, Writing, Funding acquisition. **Paul Schüle:** Methodology, Formal analysis, Writing. **Hannes Taubenböck:** Conceptualization, Funding acquisition. **Matthias Weigand:** Conceptualization, Methodology, Formal analysis, Writing.

Declaration of competing interest

The authors declare the following financial interests: This project was financially supported by the Bertelsmann foundation.

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Data availability

The data that has been used is confidential.

Acknowledgments

We gratefully acknowledge financial support from the Bertelsmann Foundation. Elisabeth Arnold, Peter Reschenhofer, Maria Riegler, Theresa Schröter, Jelena Todorovic, and Diego Alonso Alarcón Díaz provided excellent research assistance.

Appendix 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), StředníMorava (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. Fig. A.1 shows the distribution of LAU sizes in the sample region, indicating a relatively high spatial segmentation in the Czech Republic.

A.2. Remote sensing data

The remote sensing data of night light 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). DMSP-v4 yearly stable lights combine multiple observations of nighttime lights per year to reduce atmospheric and extraterrestrial influences caused by sunlight, glare, moonlight, aurora, or clouds (Baugh et al., 2010). To mitigate possible bias from short-term phenomena or extraterrestrial luminance, we use DMSP-OLS annual stable lights composites. Using several filtering techniques, this removes atmospheric and extraterrestrial influences caused by sunlight, glare, moonlight, aurora, or clouds. In addition, fire or

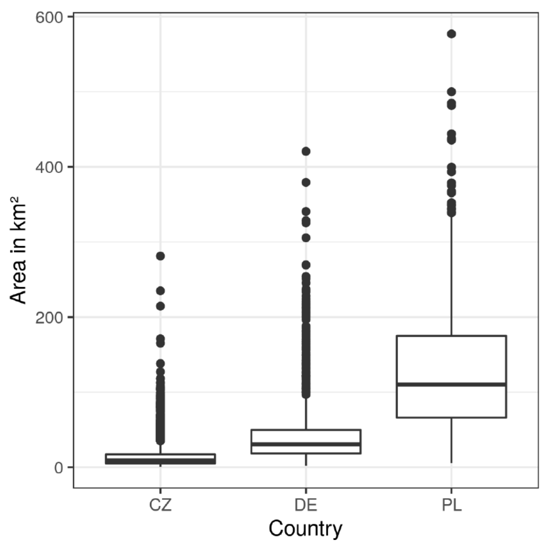


Fig. A.1. Size Distribution of Municipalities per Country in the Sample Region.
Notes: The boxplots show the size distribution of all municipalities in the sample region per country (CZ = Czech Republic, DE = Germany, PL = Poland). It is apparent that Poland (the Czech Republic) has the largest (smallest) municipalities with respect to size. Our sample region includes 3733 municipalities in the Czech Republic, 2220 municipalities in Germany and 602 municipalities in Poland.

Table A.1
Reclassification scheme for IGBP classes.

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

Notes: IGBP classes are (1) evergreen needleleaf forests, (2) evergreen broadleaf forests, (3) deciduous 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.

other short-term phenomena are removed from the stable lights yearly composite.

As shown for example by Nordhaus and Chen (2015), DMSP-OLS data are prone to time series errors when recording changes for the same spatial unit over time. This is for example due to changing amplification settings on the photomultiplier tube, e.g. over the lunar cycle, as well as due to changes in the satellites used. To avoid unreasonable conclusions from systematic biases between different yearly composites, inter-calibration is required. 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. In line with previous studies, we have chosen the 2001 composite. 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 have 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.

While DMSP-OLS data have been proven to be valuable in economic studies, they show significant blurring artifacts. These artifacts in the form of a 2D Gaussian blur (σ = 1.55 km, Abrahams et al., 2018) are spatially consistent. Opposed to previous studies mapping urban spatial extents (Zheng et al., 2020, for example), we do not reduce the blurring artifacts as we compare the aggregate sum of NTL emissions within independently defined spatial entities, i.e. LAU areas. We expect, however, the blurring to have a potential smoothing effect on spatial spillover analyses. We therefore conduct several robustness checks for our spillover analysis, (i) assessing effects for neighbors of neighbors that do not share a border with the respective municipalities and hence suffer from less blurring and (ii) focusing only on core settlement areas.

Land cover information was acquired in the form of yearly land cover data derived from images of the "Moderate Resolution Imaging Spectroradiometer" (MODIS) acquired by the Terra and Aqua satellites. The MCD12Q1.006 land cover products are accessible free of charge, including the IGBP land cover classification (see MODISUserGuide, 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 m. 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 the 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 intraregional 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 the start and end dates of the project, the location of the project or a thematic categorization of the project.

As there is no central systematic European database providing these data, we collect information from lists of beneficiaries supported by the ERDF and CF from websites of 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.[22]

[22] 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 that are part of the sample region.

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.

Country	Fund	Coverage of LAU information[a]	Total EU co-funding Amount considered	Comparison with EU payments[b]
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.

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.

[a] 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.

[b] 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.

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 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 fails to provide 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.

Appendix B. Additional figures and tables

B.1. Night light emissions and GDP growth

See Table B.1.

Table B.1
Night light emissions and GDP growth at the NUTS-3 level.

	(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

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. Growth rates are computed as the log difference between 2013 and 2007. Robust standard errors, with t-statistics shown in parentheses. Levels of significance: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

B.2. Robustness checks

See Table B.2.

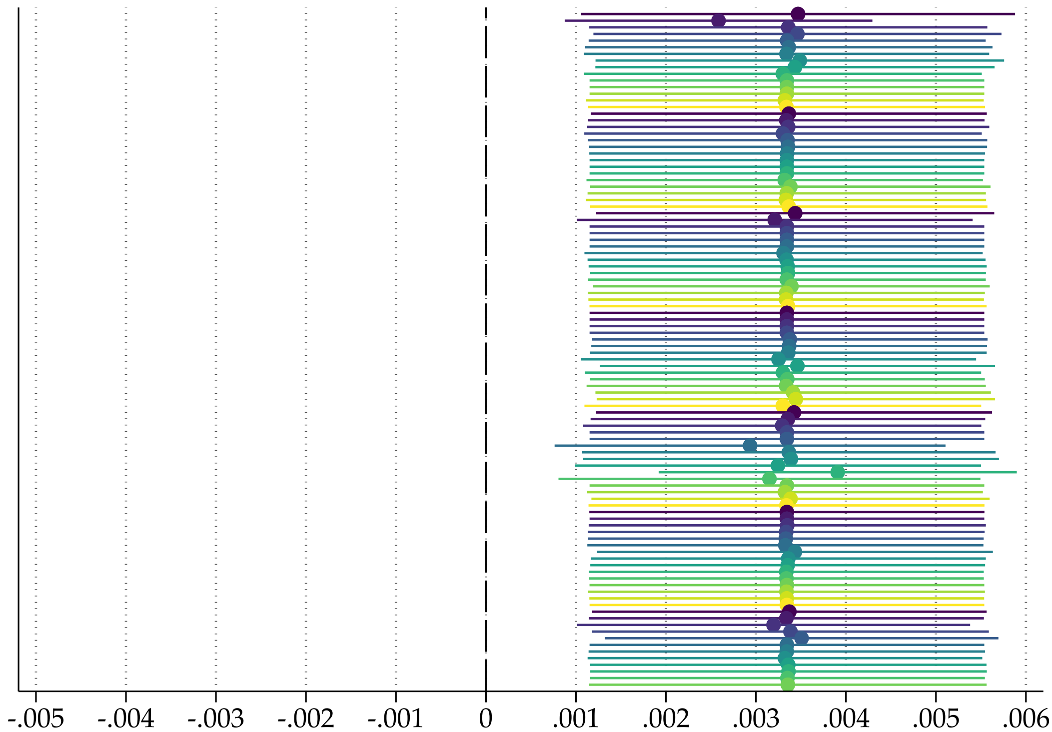


Fig. B.1. Robustness of Main Results: Exclusion of Single NUTS-3 Regions.
Notes: This figure shows baseline estimates (Column (2) of Table 3) when excluding one NUTS-3 region at a time. Estimates are slightly lower when excluding the region of Plzen (second line), but nevertheless remain broadly in line with the other estimates.

Table B.2
Robustness of main results: Different fixed effects.

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
Panel (A): Baseline				
Funding Amount	0.00251*	0.00723***	0.00742***	0.00745***
	(2.33)	(4.38)	(4.50)	(4.38)
log(NLE_2007)	−0.0145	−0.0584***	−0.0664***	−0.0694***
	(−1.45)	(−4.24)	(−4.34)	(−4.46)
Panel (B): Additional Controls				
Funding Amount	0.00176	0.00423***	0.00325**	0.00334**
	(1.71)	(3.82)	(3.07)	(3.03)
Share Urban_2007	−0.327***	−0.241***	−0.281***	−0.278***
	(−5.77)	(−5.27)	(−5.90)	(−5.49)
Share Cropland _2007	−0.113***	−0.112***	−0.127***	−0.136***
	(−4.33)	(−4.25)	(−5.09)	(−5.08)
log(Population)	0.143***	0.125***	0.126***	0.126***
	(6.04)	(6.10)	(5.99)	(5.95)
log(NLE_2007)	−0.170***	−0.180***	−0.181***	−0.184***
	(−5.74)	(−6.05)	(−5.89)	(−5.89)
Country FE	–	✓	–	–
NUTS-2 FE	–	–	✓	–
NUTS-3 FE	–	–	–	✓
Observations	6555	6555	6555	6555

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), employing different kinds of fixed effects. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. Column (1) does not include any fixed effects. Column (2) includes country fixed effects, Columns (3) includes NUTS-2 fixed effects and Column (4) NUTS-3 fixed effects. In Panel (A), we control only for the initial log nighttime light emission at the start of the funding period. In Panel (B), we add the share of urban and cropland area and log population, all measured in 2007 at the municipality level. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Alternative specifications. We use numerous alternative specifications as a robustness check. First, Columns (1) and (2) in appendix Table B.3 report significantly positive effects when using the untransformed funding amount in million Euros instead. At an average funding amount of 4.379 million Euros over 7 years (see Table 1), the estimated impact of increasing funding by 1% is smaller than in our baseline specification in Table 3. This difference is likely driven by a non-linear effect of funding in Euros combined with a skewed distribution of funding amounts. Second, using the number of projects that were funded in the period 2007–2013 as the main regressor instead of the total funding amount also yields a positive and significant association with night light emission growth (Table B.3, Columns (3) and (4))

Third, Table B.4 (Columns (1) and (2)) displays a robustness check using a population-weighted average for funding rather than equally splitting funding across multiple municipalities. Fourth, we test for effects at the intensive margin by using the log transformation. With many zeros in the data, using $ln(0)$ drops all municipalities that received no funding at all and limits our sample to municipalities that attain funding. As shown in Table B.4 Columns (3) and (4), estimates approximately double when only considering the intensive margin. Results using $ln(X+1)$ are comparable to our baseline specification (available upon request).

Assessing pre-trends and selection effects. We conduct several exercises to assess pre-trends and the extent of possible selection effects. First, Fig. B.2 displays percentage changes in annual NLE for municipalities that received funding in 2007–2013 either below or above the median funding amount. While these municipalities did not follow exactly the same trends before the start of the funding period, there is no evidence that municipalities with above median funding amounts exhibited higher growth rates prior to 2007. After 2007, municipalities with above median funding grew considerably stronger than municipalities with below median funding, consistent with our baseline results.

Second, we conduct a placebo exercise, estimating the funding effect on the growth in night light emissions in the preceding period. As shown in Table B.5, the amount of funding a municipality received in 2007–2013 has no predictive power for the growth in NLE in the seven years from 2000–2006, before municipalities received funding.

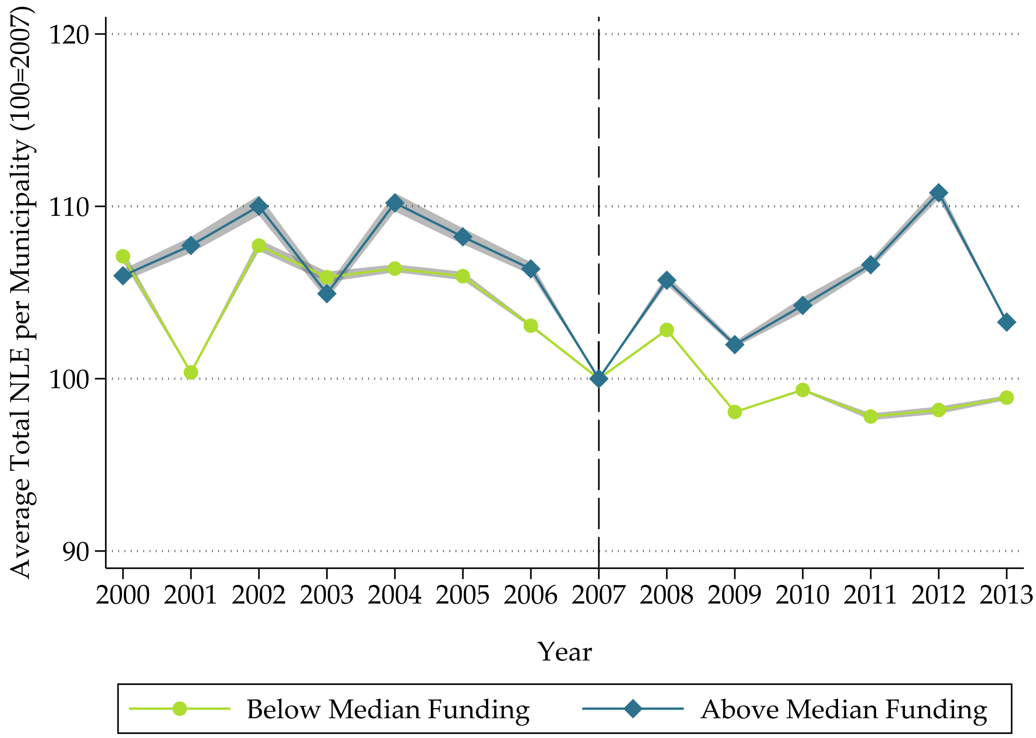


Fig. B.2. Changes in Nightlight Emissions for Municipalities Below and Above the Median Funding Amount.
Notes: This figure shows the development of average total yearly NLE for municipalities with received funding in 2007–2013 either below or above the median funding amount. To allow for a better comparison of both series, they are divided by their 2007 value to index them to 1 in this year. Gray shaded areas indicate pointwise 95% confidence intervals.

Table B.3
Night light growth and alternative measures of EU funding I.

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
Funding Amount Mill. Euro	0.000875***	0.000375***		
	(4.12)	(3.90)		
Number of Projects			0.000287**	0.000157***
			(2.71)	(3.75)
$\log(NLE_{2007})$	−0.0610***	−0.183***	−0.0595***	−0.183***
	(−4.08)	(−5.89)	(−4.07)	(−5.89)
Share Urban$_{2007}$		−0.290***		−0.290***
		(−5.54)		(−5.58)
Share Cropland$_{2007}$		−0.138***		−0.138***
		(−5.05)		(−5.07)
log(Population)		0.129***		0.129***
		(6.06)		(6.04)
NUTS-3 FE	✓	✓	✓	✓
Observations	6555	6555	6555	6555

Notes: This table reports the estimates of a regression of the growth in log night light emission in the period 2007–2013 on either the total funding amount in million Euros received by each municipality, or 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. Other than in Table 3, we do not apply any transformation to the funding amount and capture linear effects of funding in Columns (1) and (2). In Columns (3) and (4), we use the absolute number of funded projects as explanatory variable instead. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B.4
Night light growth and alternative measures of EU funding II.

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
IHS(Funding Amount)	0.00797***	0.00312**		
	(4.43)	(2.78)		
log(Funding Amount)			0.0165***	0.00765**
			(4.19)	(2.73)
$\log(NLE_{2007})$	−0.0713***	−0.184***	−0.0726***	−0.170***
	(−4.44)	(−5.88)	(−4.27)	(−5.68)
Share Urban$_{2007}$		−0.277***		−0.255***
		(−5.49)		(−5.62)
Share Cropland$_{2007}$		−0.136***		−0.133***
		(−5.08)		(−4.51)
log(Population)		0.125***		0.111***
		(5.97)		(5.89)
NUTS-3 FE	✓	✓	✓	✓
Observations	6555	6555	5692	5692

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. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. In Columns (1) and (2), in case of joint projects, funding is assigned to municipalities according to population weights, rather than assigning the unweighted average. As in Table 3, funding amounts transformed by inverse hyperbolic sine transformation (IHS). In Columns (3) and (4), other than in Table 3, the funding amount was log-transformed. The latter limits our sample to the intensive margin with only municipalities that receive positive funding. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

This confirms that our findings are not merely driven by a spurious correlation between EU funding and NLE.

Third, our baseline estimates barely change when controlling for lagged growth in NLE (Table B.6).

Addressing blurring in spillovers. Spatial blurring, i.e., a diminished spatial precision at a small geographic scale, may at least partly affect spillover estimates. In addition to our neighbors of neighbors estimates in Table 4, Table B.8 addresses blurring by measuring night light emissions only in the core settlement areas of municipalities and neighboring municipalities. This settlement area is derived from the Global Urban Footprint (GUF) Product, a binary mask of built-up settlement areas worldwide (Esch et al., 2017). As the core settlement area typically lies in the center of a municipality, this excludes night light emissions in bordering areas, where blurring from neighboring municipalities

Table B.5
Placebo estimates—does funding predict past growth?

	(1) ΔNLE 2000–2006	(2) ΔNLE 2000–2006
Funding Amount	−0.000206	0.00116
	(−0.23)	(1.20)
$\log(NLE_{2007})$	0.0411**	0.0836**
	(2.92)	(3.31)
Share Urban_{2007}		0.371***
		(6.08)
Share Cropland_{2007}		0.115**
		(3.25)
log(Population)		−0.0500*
		(−2.60)
NUTS-3 FE	✓	✓
Observations	6555	6555

Notes: This table reports the estimates of a regression of the growth in log night light emission in the period 2000–2006 on the total funding amount received by each municipality in 2007–2013 (transformed using the inverse hyperbolic sine transformation) and controls. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table B.6
Baseline results controlling for lagged night light growth.

	(1) ΔNLE	(2) ΔNLE
Funding Amount	0.00741***	0.00349**
	(4.50)	(3.19)
$\log(NLE_{2007})$	−0.0628***	−0.174***
	(−4.06)	(−5.93)
ΔNLE 2000–2006	−0.160***	−0.123***
	(−3.80)	(−3.59)
Share Urban_{2007}		−0.232***
		(−4.89)
Share Cropland_{2007}		−0.121***
		(−4.45)
log(Population)		0.120***
		(6.35)
NUTS-3 FE	✓	✓
Observations	6555	6555

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, including lagged NLE growth. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table B.7
Funding Effect in Different Years.

	Finished before 2013		Ongoing in 2013		Funded in 2007–2009	
	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE	(5) ΔNLE	(6) ΔNLE
Funding Amount	0.00319**	0.00237*	0.00324**	0.00210*	0.00662***	0.00301***
	(2.86)	(2.37)	(3.25)	(2.43)	(4.97)	(3.98)
$\log(NLE_{2007})$	−0.0573***	−0.182***	−0.0568***	−0.182***	−0.0669***	−0.184***
	(−3.96)	(−5.88)	(−3.94)	(−5.87)	(−4.34)	(−5.89)
Share Urban_{2007}		−0.283***		−0.282***		−0.277***
		(−5.55)		(−5.51)		(−5.51)
Share Cropland_{2007}		−0.138***		−0.138***		−0.136***
		(−5.06)		(−5.04)		(−5.03)
log(Population)		0.130***		0.130***		0.126***
		(6.08)		(6.07)		(5.99)
NUTS-3 FE	✓	✓	✓	✓	✓	✓
Observations	6555	6555	6555	6555	6555	6555

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 for projects that are finished before 2013 (transformed using the inverse hyperbolic sine transformation), for projects that are still ongoing in 2013 (transformed using the inverse hyperbolic sine transformation), or funds received by each municipality in the years 2007–2009 (transformed using the inverse hyperbolic sine transformation) and controls. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table B.8
Spillover effects from funding in neighboring municipalities: Focus on core settlement areas.

	(1) ΔNLE	(2) ΔNLE
Funding Amount	0.00836***	0.00409**
	(4.89)	(2.90)
Funding Amount in Neighboring Municipalities	0.00276	0.00340*
	(1.55)	(2.24)
Funding Amount Neighbors of Neighbors	0.00543	0.00319
	(1.49)	(1.02)
$\log(NLE_{2007})$	−0.0748***	−0.196***
	(−4.00)	(−5.76)
Share Urban$_{2007}$		−0.327***
		(−6.58)
Share Cropland$_{2007}$		−0.146***
		(−6.90)
log(Population)		0.134***
		(6.03)
NUTS-3 FE	✓	✓
Observations	6546	6546

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 in the core settlement area of 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 variables *funding amount in neighboring municipalities* and *funding amount neighbors of neighbors* are computed as the sum of funding received by, respectively, all directly adjacent municipalities and all neighbors of adjacent municipalities (and transformed using the IHS) and indicate the size of spillover effects. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B.9
Funding effect by type of fund—ERDF, CF, INTERREG.

	ERDF		CF		INTERREG	
	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE	(5) ΔNLE	(6) ΔNLE
Funding Amount	0.00674***	0.00299***	0.00566***	0.000825	0.00442***	0.00353***
per Fund	(4.76)	(3.53)	(3.56)	(0.78)	(4.96)	(5.20)
$\log(NLE_{2007})$	−0.0679***	−0.183***	−0.0699***	−0.182***	−0.0613***	−0.186***
	(−4.40)	(−5.88)	(−4.43)	(−5.87)	(−4.17)	(−5.97)
Share Urban$_{2007}$		−0.278***		−0.277***		−0.285***
		(−5.51)		(−5.52)		(−5.53)
Share Cropland$_{2007}$		−0.137***		−0.137***		−0.133***
		(−5.03)		(−5.13)		(−5.00)
log(Population)		0.126***		0.128***		0.130***
		(5.95)		(6.05)		(6.11)
NUTS-3 FE	✓	✓	✓	✓	✓	✓
Observations	6555	6555	6555	6555	6555	6555

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 ERDF, CF and INTERREG funding amount, respectively, 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. Standard errors are clustered at the NUTS-3 level, with t-statistics in parentheses. Levels of significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

should arguably be more important. Reassuringly, results look similar compared to our baseline estimates.

B.3. Baseline results for ERDF, cohesion fund and INTERREG amounts

Table B.9 shows results for separate estimations for the ERDF (columns 1 and 2), Cohesion Fund (columns 3 and 4) and INTERREG projects (columns 5 and 6).

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