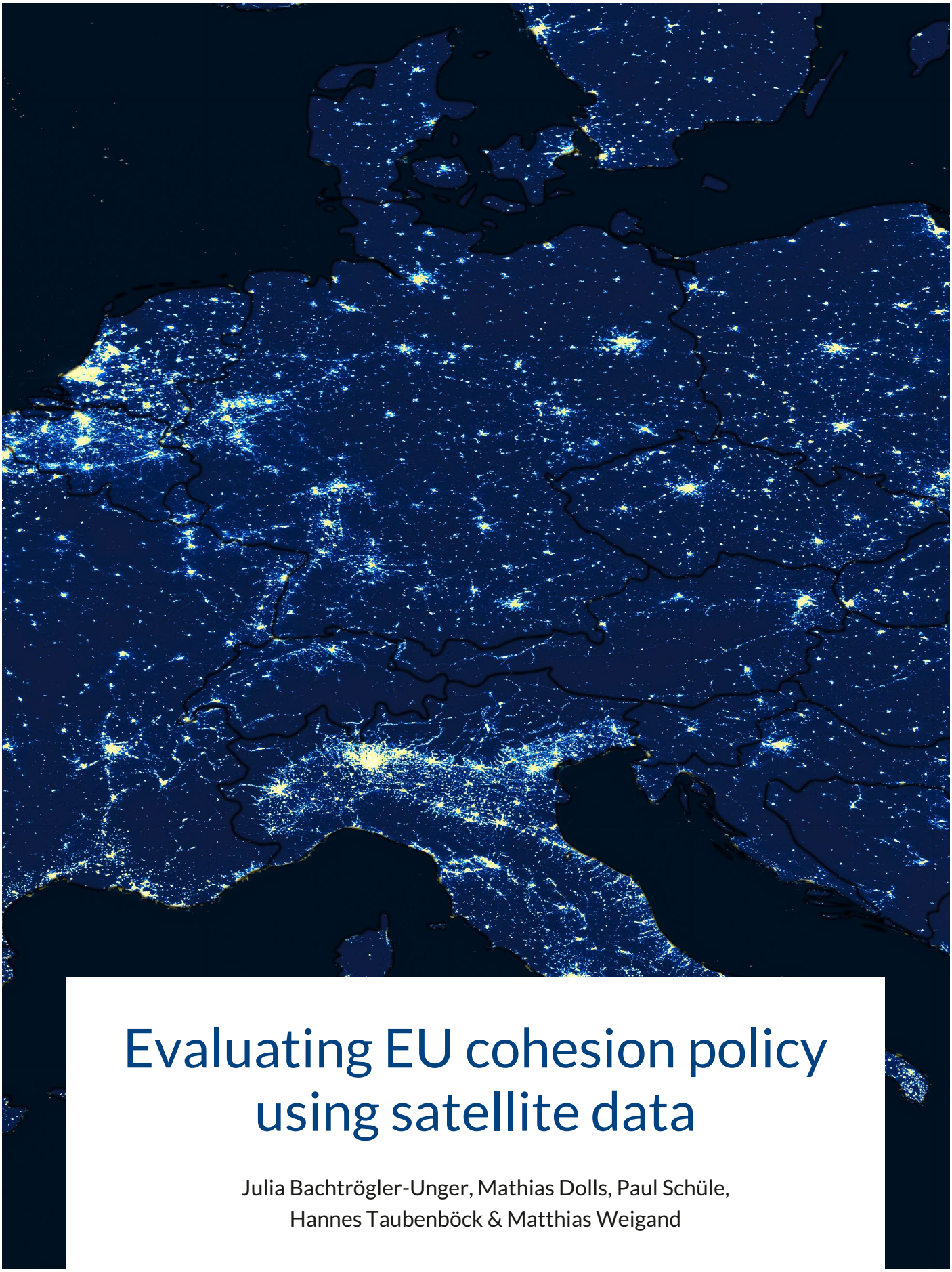

Evaluating EU cohesion policy using satellite data

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BertelsmannStiftung

About the project

Within the “Europe’s Future” program, the project “Repair and Prepare: Strengthening Europe” delivers ideas and analyses for a stronger European economy.

The interdisciplinary module “Europe seen from the stars” uses satellite data to evaluate how EU funding (structural and cohesion funds) in the periods 2007–2013 and 2014–2020 has affected infrastructural changes and economic growth in a pilot region containing municipalities in Germany, Poland and the Czech Republic. A further component is a qualitative case study evaluation, which allows to get an impression of the concrete development of the local economic situation.

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Evaluating EU cohesion policy using satellite data

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Abstract

In December 2020, the Council of the European Union adopted the EU's long-term budget for the years 2021 to 2027. With a share of 31 percent of the total budget (around 330 billion Euro), cohesion policy remains an important priority area. Given the large amount of resources dedicated to reduce economic and social disparities between European regions, it is essential to learn about the impact of different funding instruments in previous budgetary periods. In this project, we illustrate a novel approach of evaluating the economic effects of the European Regional Development Fund and the Cohesion Fund since 2007. For a selected pilot region in the border area of the Czech Republic, Germany and Poland we collect data on EU funding at the municipality level. Using night light emission data as a proxy for economic development, we show that the receipt of a higher amount of EU funding is associated with higher growth in these areas. The results of this project suggest that remote sensing data can be used effectively to capture the small-scale impact of place-based policies on economic development, even in a pan-European context.

Zusammenfassung

Im Dezember 2020 hat der Rat der Europäischen Union die Verordnung zur Festlegung des Mehrjährigen Finanzrahmens 2021-2027 angenommen. Mit einem Anteil von 31 Prozent am Gesamthaushalt (rund 330 Mrd. Euro) bleibt die Kohäsionspolitik ein zentraler Schwerpunktbereich der EU. Angesichts der umfangreichen Mittel, die für den Abbau wirtschaftlicher und sozialer Ungleichheiten zwischen den europäischen Regionen bereitgestellt werden, ist es wichtig, aus empirischen Erkenntnissen über die Auswirkungen der Regionalförderungen in früheren Haushaltsperioden zu lernen. In diesem Projekt entwickeln wir einen neuen Ansatz, um die Effekte des Europäischen Fonds für Regionale Enwicklung und des Kohäsionsfonds auf das regionale Wirtschaftswachstum seit 2007 zu schätzen. Für eine ausgewählte Pilotregion im Grenzgebiet von Deutschland, Polen und Tschechien erheben wir Daten zur EU-Förderung auf Gemeindeebene. Unter Verwendung von Nachtlichtdaten zur Erfassung der wirtschaftlichen Entwicklung zeigen wir, dass der Erhalt eines höheren Förderbetrags mit höherem Wachstum einhergeht. Die Ergebnisse dieses Projekts zeigen, dass Fernerkundungsdaten effektiv genutzt werden können, um die kleinräumigen Auswirkungen regionaler Wirtschaftsförderung auch im gesamteuropäischen Kontext zu quantifizieren.

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1 Introduction

In December 2020, the Council of the European Union adopted the Regulation establishing the EU's multiannual financial framework (MFF) for the years 2021 to 2027 with a total expenditure of 1074 billion Euro, as well as the Next Generation EU recovery instrument (NGEU) worth 750 billion Euro to fight the consequences of the COVID-19 pandemic. Around 60% of both the NGEU and the MFF is dedicated to the policy area "cohesion, resilience and values". Thus, EU regional policy to promote economic, social and territorial cohesion among regions remains a key long-term priority. As in the MFF 2014-2020, cohesion policy is the second largest budget item (after the Common Agricultural Policy): The European Regional Development Fund (ERDF), the European Social Fund+ (ESF+) and the Cohesion Fund (CF) account for 31% of total expenditure in the MFF 2021-2027 (330 billion Euro), with by far the highest amount allocated to the ERDF (200 billion Euro).

In the MFF 2014-2020, around 346 billion Euro of structural and cohesion funds were allocated to European regions,[1] of which more than half was targeted at less developed regions.[2] While in recent decades the focus of cohesion policy has shifted from increasing economic growth to smart, inclusive and innovative growth, supporting GDP growth in less developed European regions, with a GDP per capita below 75% of the EU average, and fostering regional competitiveness and employment remain major policy objectives.

There exists a large academic literature which tries to investigate whether this money is well spent. However, evaluating the impact of EU funding on economic growth is challenging. Given the lack of better data, previous literature has largely studied the growth effects of funds at the level of NUTS-2 or NUTS-3 regions,[3] where it is hard to disentangle the impact of EU funds from other regional trends. As a consequence, there is still no consensus on the effectiveness of EU cohesion policy. While Beugelsdijk & Eijffinger (2005), Maynou et al. (2016), Rodríguez-Pose & Fratesi (2004), Cappelen et al. (2003) and Cerqua & Pellegrini (2018*a*) all report a positive association between funding and growth, Boldrin & Canova (2001), Fagerberg & Verspagen (1996), Dall'Erba & Le Gallo (2008) and Eggert et al. (2007) find insignificant or even negative effects. In a meta-analysis, Dall'Erba & Fang (2017) review the quantitative evidence of 17 studies which estimate growth elasticities. The average estimate is positive but close to zero at 0.174 and estimates range from -7.6 to 6.3.

Recently, a series of studies has advanced this literature methodologically by the use of a regression discontinuity design. Becker et al. (2010), Becker et al. (2018), Pellegrini et al. (2013) and Cerqua & Pellegrini (2018*a*) exploit the fact that regions are eligible for higher amounts of cohesion policy funding once their GDP per capita exceeds the threshold – the single criterion to be classified as a less developed region. The assumption here is that regions close to the threshold face economically very similar conditions and effectively only differ in their eligibility for EU funding. Comparing NUTS-2 regions at both sides of the cut-off, these studies find that EU funding fosters economic growth.

[1] See https://cohesiondata.ec.europa.eu/overview.

[2] See https://ec.europa.eu/regional_policy/en/funding/available-budget.

[3] This report follows the *Nomenclature of territorial units for statistics* (NUTS) 2016 classification.

Our approach is distinct, as we estimate the funding impact on a spatially much more granular level. For a pilot region in the border area of Germany, Poland and the Czech Republic, we draw on a new project database of funding activity which allows one to observe the detailed distribution of EU funds in the MFFs 2007-2013 and 2014-2020 among local administrative units (LAUs). LAUs are maintained by Eurostat and comprise the municipalities and communes of the European Union.[4] At the level of LAUs, there is no systematic differentiation between different policy intensities or targets such as the 75%-threshold of GDP per capita below which NUTS-2 regions become eligible for the convergence objective or a smart specialization strategy designed for a NUTS-2 region. This means that funding estimates at the municipality level are expected to be less confounded by third factors than in analyses at NUTS-2 level. Moreover, this approach will allow new insights into the regional variation of policy effectiveness across NUTS-2 regions that no longer relies on regional characteristics but reflects heterogeneous factors at the municipality level. This has been under-researched so far.

To assess the impact of funding at such a granular level, we leverage the potential of remote sensing data. In doing so, we are guided by the hypothesis that increased economic growth is accompanied by changes in spatial-structural parameters. In particular, we proxy the development of local economic activity by changes in the night light emission of a given municipality over time. It has been shown that night light emission data have the potential to approximate economic conditions (e.g. Jean et al. 2016, Mellander et al. 2015). We apply this proxy because as of today, for most member states there is no information on GDP or other measures of economic activity available at the municipal level. In addition, we consider other indicators retrieved from satellite imagery like the degree of urbanization or changes in vegetation density.

To the best of our knowledge, this project is the first to ground an analysis of EU cohesion policy at such a spatially granular level and to cover large areas across administrative units as well as programming periods. Based on these data we document considerable variation in funding across time and space. 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 night light emission. Keeping this measure of initial economic activity constant, funding is more likely to flow to municipalities with a higher population as well as lower levels of cropland. With our data we also uncover systematic differences in the quantity and quality of funding across countries and over time. For example, we find that municipalities in Poland carried out much larger individual projects (in terms of median EU funding per project) than municipalities in Germany or the Czech Republic. This can be explained by the fact that the lion's share of funding in Poland went to the creation of new transport infrastructure like roads or railways, which constitute a

[4] There are only a few studies which have followed a similar approach: Mayerhofer et al. (2020) have analyzed European Structural and Investment Funds in Austria since 1995 at the municipality-level using (not publicly available) project-level data provided by Austrian authorities. Cerqua & Pellegrini (2018*b*) have performed a causal evaluation of cohesion policy for Italian regions using project-level data at the municipality level, however, with conclusions drawn for a less granular regional level. At the beneficiary-level, Bachtrögler, Fratesi & Perucca (2020) have investigated the effectiveness of structural funds on the performance of supported manufacturing firms in seven EU member states and find that the effects differ across countries, different types of regions and outcome indicators.

particularly costly type of project. Patterns like this may help to broaden our understanding of why prior literature has found such large heterogeneity in the effectiveness of EU cohesion policy across countries and regions.

We then investigate if municipalities which received more funding experienced a higher increase in night light emission during a programming period. All else equal, in the period 2007-2013 receiving 1% more of EU funding was associated with a 0.007% higher growth in night light emissions. For the second programming period 2014-2020, we find that a 1% funding increase was associated with 0.01% higher growth of night light emissions. This association between funding and growth turns out to be even higher when spill-over effects from higher funding in neighbouring municipalities are taken into account. This demonstrates that our approach to capture funding effects by satellite imagery can seize the effectiveness of funding at a very local level. Although we try to mitigate concerns about endogeneity of funding by municipality as carefully as possible, at the moment our data do not enable us to cleanly identify any causal impact of EU funding on economic growth. Instead, this study serves as a pilot analysis investigating how novel small-scale data can help in targeting important questions of regional and place-based policies.

In addition to contributing to the voluminous literature on the effects of EU cohesion policy, the project constitutes an encouraging example of how remote sensing data can be leveraged for evaluating place-based economic policies. Satellite imagery is famous for providing a bird's eye view on processes upon the Earth's surface. In recent years for example, studies have documented changes on the land surface (e.g. Taubenböck et al. 2012, Leichtle et al. 2017). Beyond that, a rapidly growing body of literature draws on satellite imagery for analyzing economic questions (see Donaldson & Storeygard 2016, for a recent review). Most prominent have been applications where GDP growth has been proxied with night light emissions (e.g. Jean et al. 2016, Mellander et al. 2015), as in this study. For instance, they have been used to delineate economically strong regions (e.g. Florida et al. 2008, Taubenböck et al. 2017, Georg et al. 2018) or with the underlying aim of analyzing real regional GDP without any measurement errors (e.g. Gennaioli et al. 2014). Most of these studies, though, tend to focus on the comparison of larger administrative units like countries (Henderson et al. 2012) or, in Europe, NUTS-1 regions (Lessmann & Seidel 2017). We focus on a much finer level of spatial detail. We also note that most prior studies using night lights focus on developing countries, where GDP estimates may be unreliable even at federal or state level. In this project, we use night lights to fill a different type of data gap: While in Europe information on GDP and other central indicators is available up to the NUTS-3 level, there is no information available at the more granular municipality level.

This project report is organized as follows. In Section 2, we illustrate in a case study approach how remote sensing data can be leveraged to detect the impact of EU funding on a very regional level. Section 3 describes our data sources as well as the pilot region we study in this analysis. Section 4 analyses the spatial distribution of EU funding among the municipalities of the pilot region. In Section 5, we demonstrate that night light emission data correlate highly with GDP and are thus valuable proxies for economic activity at local level. In Section 6, we test

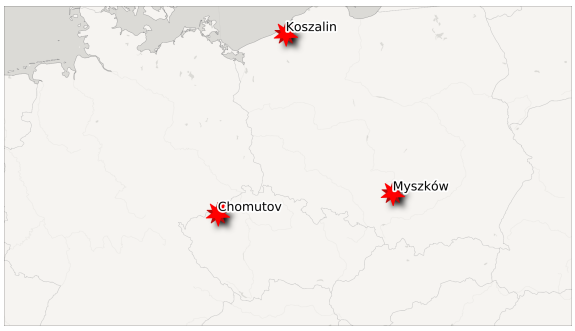
if economic conditions at the municipality level have been converging during the analysis period, before we turn to evaluating the impact of EU funding in Section 7. Section 8 summarizes our findings and discusses how the insights of this project may prove valuable for future research and policy work.

2 Motivation

Most EU citizens have at least seen one building, road or bridge under construction that was partially funded by the EU. From the ground, one can see heavy machinery operating to remove trees and meadows and pave the way for a road or building. Once finished, in the best case the new built infrastructure ideally serves to develop economic growth in the town, city or even region.

What might be clear to see on the ground and may be known to many locals, is, however, difficult to assess on a broader regional, national or even continental scale. It therefore seems tempting to search for data able to capture local changes but on a large scale. In the following, three examples of different EU-funded projects that are visible from space highlight why we adopted the procedure used during the project. Figure 1 shows the location of the three cities in Poland and the Czech Republic.

Figure 1: Location of three example cities Myszków and Koszalin in Poland, Chomutov in the Czech Republic



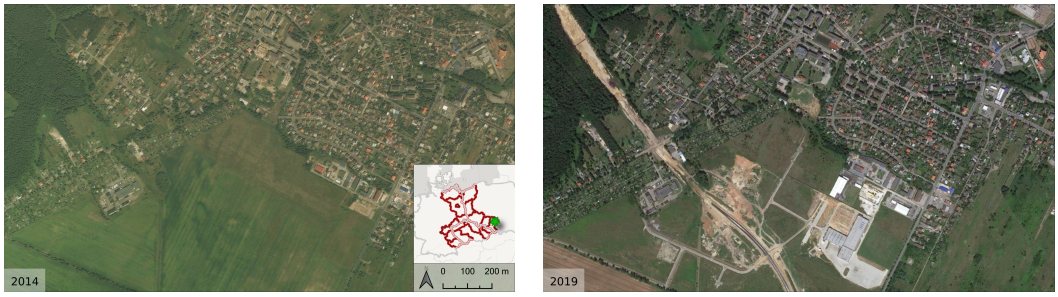
As a first example, Figure 2 shows the town of Myszków, Poland, where a bypass was built using EU funding in the project "Reconstruction of D 791 on the section from DK 1 to DK 78, stage I construction of the bypass of the village of Myszków".[5] Figure 2 a) and b) show the town before and after the construction of the bypass west of the town in 2014 and 2019, respectively. As a direct consequence of the new road, a commercial area was created alongside the bypass. As early as 2019, businesses started settling there and more are expected in due course. This highly detailed view reveals how this project has triggered landscape change linked to economic development.[6] These highly detailed aerial images, however, are, if available at

[5] This project is also the partner study "European funding policy in Poland, the Czech Republic and Germany" (published in German as *"Europäische Förderpolitik in Polen, Tschechien und Deutschland"*)

[6] Note that we do not know if businesses have moved there from other parts of the city.

large scale at all, very cost-intensive. What's more, analyzing such high resolution imagery in a national or continental scale would require immense computational resources. Therefore, limiting the spatial detail to that of freely available satellite data is unavoidable if one is to increase applicability to cover large areas.

Figure 2: EU-funded construction of a bypass road as seen from satellite images in Myszków, Poland



(a) 2014 **(b)** 2019

Notes: The images show the construction site of a bypass road in the town Myszków, Poland, as seen from very high resolution optical satellite imagery. The images were taken in 2014 and 2019, respectively. As a result of the improved infrastructure, alongside the newly built bypass, a commercial site develops seen in the southern part of the image in 2019. Map data © 2021 CNES/Airbus, Google.

Data about night light emissions or spectral vegetation indices as well as land cover maps have often been used to monitor such developments from space. They have proven to provide reliable and comparable information about land surface changes across large regions (Chang et al. 2020). When comparing the amount of night light emissions in 2014 and 2019 in the small town of Myszków (cf. Fig. 3 a) and b)), local developments can also be directly and clearly linked to changes in these satellite data. The creation of commercial areas in the south led to an increase in night light emissions, while emissions from the town itself remained relatively stable.

Equally, the decline in vegetation cover measured by changing spectral reflections from the Earth's surface (see Figure 4) and caused by clearing woodland and building works is manifestly significant. Again, the rest of the town remained relatively unchanged over the period. These examples based on different satellite data or derived mapping products show how even coarse satellite imagery is a valuable tool for identifying and measuring the impact of economic development on a given locality.

Similar changes in land cover in close spatial and temporal proximity to EU-funded construction projects can be found in other regions as well. For example, after building a new bypass and link in the Czech town of Chomutov, commercial areas to the south and west of the town were expanded (see Figure 5). In the city of Koszalin, Poland, similar developments

Figure 3: Increase of night light emissions over Myszków, Poland

(a) 2014 **(b)** 2019

Notes: The images show night light emissions before and after the construction of the bypass road in the town Myszków, Poland. The images were taken in 2014 and 2019, respectively. Low emissions are indicated by blue colored overlay, yellow colors indicate high night light emissions. In the area of the newly developed commercial area, an increase in night light emissions can be seen, while the emissions in the rest of the town remain relatively stable. Basemap Map data © 2021 CNES/Airbus, Google.

Figure 4: Reduction of vegetation index in Myszków

Notes: This image shows the difference in vegetation activity in Myszków, Poland, between 2014 and 2019 as measured by the normalized difference vegetation index (NDVI, see Section 3.2.1). High decrease in vegetation activity can be found in the areas where construction as indicated by orange and red colors. Vegetation cover and activity was stable in the central town area, indicated by yellow to light green colors. Basemap Map data © 2021 CNES/Airbus, Google.

can be seen (see Figure 6).

Land cover change on the Earth's surface associated with these example projects can be observed and quantified by utilizing modern long-running time series of satellite imagery. When aggregating all information in the continuous time series, it is possible to derive trends from the data and reduce effects of seasonality or annual anomalies.

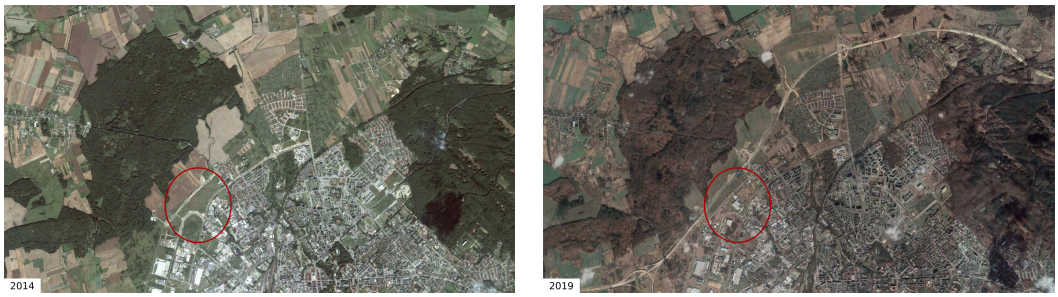
Yet, the aforementioned examples are infrastructure projects, which are bound to have a notable direct impact on the surrounding land cover or night light emissions that is visible in satellite data. At the same time, EU funding is also available for research & development and innovation or productive investment and business support. But with these types of funding the impacts on satellite data, i.e. increased nighttime light emissions or changes in vegetation

Figure 5: Project for the construction of a new road and connection in Chomutov, Czech Republic

(a) 2006 **(b)** 2018

Notes: The comparison between two satellite images from 2006 and 2018 documents the changes in the built environment in the Czech town Chomutov that can be associated with the project "New communication from Chomutov". Highlighted in the red circles: new commercial areas; new road visible center-left (2018 image). Map data © 2021 GEODIS Brno, Maxar Technologies, Google

Figure 6: Example of the project in Koszalin, Poland and associated land cover change



(a) 2014 **(b)** 2019

Notes: Alongside the newly built highway north of Koszalin, Poland, as part of the project "Construction of the S6 expressway Szczecin — Koszalin, Koszalin ring road (S6/S11)". Highlighted in the red circles: new commercial areas; new highway visible north of the city (2019 image). Map data © 2021 Maxar Technologies, Google

cover, are likely to mirror long-term effects of increased economic activity rather than instantaneous effects that new infrastructure might have. To provide comprehensive insight into the impact of EU funding on satellite-based measurements of environmental properties, we develop quantitative analyses over a wide range of municipalities. Building on the examples above, enables one to find robust quantitative relationships between EU funding amount, economic development and environmental change. After all, a goal of this research is to find suitable proxy information for local economic development triggered by EU funding that can be derived from large-scale satellite imagery and then applied internationally.

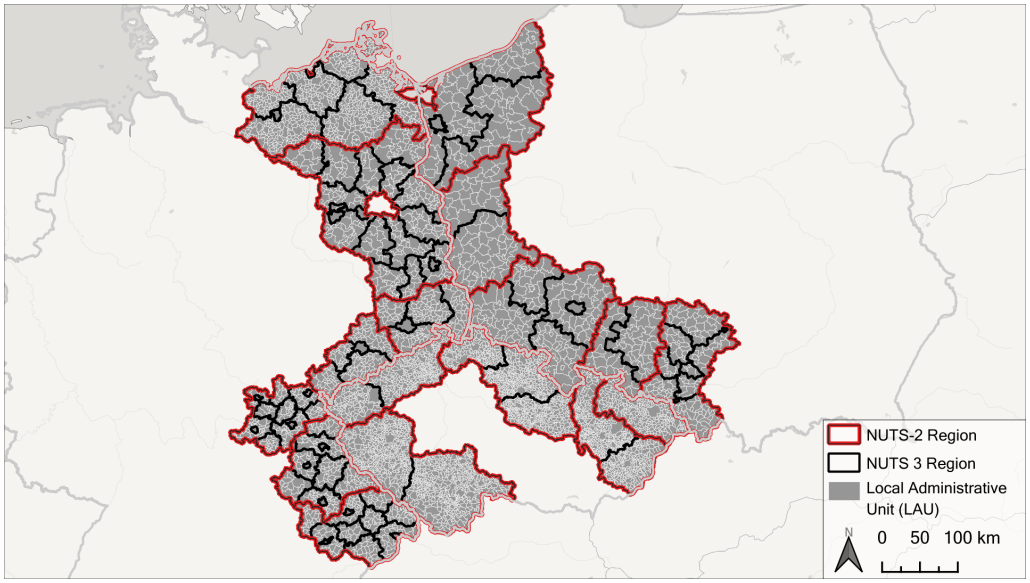
3 Data

This Section describes the data used in our analysis to quantify the impact of funding on economic conditions in our pilot region. We use EU project funding data level as provided by managing authorities of cohesion policy programs (Section 3.1), satellite imagery and other geographical data (Section 3.2), and regional economic data from national statistical offices (Section 3.3). All are made available in different spatial units. In order to combine these data sets meaningfully, a mutual and uniform spatial unit is required. Our goal is to perform the intersection on the most granular spatial unit possible. Therein we rely on data designed for geostatistical purposes provided by the statistical office of the European Union (Eurostat). The Nomenclature for Territorial Units for Statistics (NUTS) divides member states into small (administrative) units at multiple levels, thereby providing a unified framework encompassing a vast range of data that create the foundation of official European statistics.

In this study we focus on the following NUTS-2 regions in the border region between the Czech Republic, Germany and Poland (see also Figure 7):

- CZ03 (Jihozápad), CZ04 (Severozaápad), CZ05 (Severovýychod), CZ07 (Střední Morava), CZ08 (Moravskoslezsko)
- DE22 (Niederbayern), DE23 (Oberpfalz), DE24 (Oberfranken), DE40 (Brandenburg), DE80 (Mecklenburg-Vorpommern), DED2 (Dresden), DED4 (Chemnitz)
- PL22 (Śląskie), PL42 (Zachodniopomorskie), PL43 (Lubuskie), PL51 (Dolnośląskie), PL52 (Opolskie)

Figure 7: Overview of the pilot region and different NUTS level spatial entities



Our pilot region thus comprises less developed NUTS-2 regions (e.g. in Poland) and those with a relatively high GDP per capita as compared to the EU average (such as Bavaria, Germany). In addition to the regional heterogeneity in terms of economic development, this set of NUTS-2 regions enables one to investigate potential differences in the distribution of EU funding and their effects across regions in different EU member states, with different institutional systems and therefore different administrative structures to implement EU cohesion policy. For the region under investigation, multi-sensoral high-resolution satellite images are available for the years 2007 to 2019.

Previous studies performed analyses up to the NUTS-3 level (compare Dall'Erba & Fang 2017), which corresponds to counties or districts. Given the mixed evidence in these studies, the contribution of this project is to increase the level of spatial detail by focusing on more local changes. Therefore, we use the smallest entities within the NUTS scheme, Local Administrative Units (LAU), which represent the municipalities and communes of the European Union.[7] Figure 7 shows the different NUTS regions in the region under investigation. For this study we used the LAU units for the year 2018. While our pilot region comprises 17 NUTS-2 regions and 102 NUTS-3 regions, there exist 6571 LAUs. This means that even though our project is constrained to only a sub-region of Europe, we expect much more variation in funding than previous studies.

3.1 Data on EU Funding

In this study, we explore the effects of projects co-financed by the European Regional Development Fund (ERDF) and the Cohesion Fund (CF).[8] The data on EU funding includes projects funded under the objective of European Territorial Integration, i.e. projects initiated in cross-border, transnational and interregional co-operation programs (INTERREG). As they are co-financed by the ERDF, they are part of the ERDF projects analyzed in the following. At this stage, we consider 17 border NUTS-2 regions in the Czech Republic (6), Germany (7) and Poland (5) that form our pilot region.

Information on the distribution of EU regional funds to both projects and beneficiaries within European regions is available from 2007 onward. In the MFF 2007-2013, managing authorities of operational programs designed to implement the EU's cohesion policy were first required to publish lists of (public and private) beneficiaries of the ERDF and the CF. By regulation (Article 7 of Commission Regulation (EC) No 1828/2006), these lists had to include the name of the operation and the amount of (EU and national) public funding allocated to the operation. For the MFF 2014-2020, Regulation (EU) No 1303/2013 (Annex II) sets more comprehensive minimum requirements for the content and form of the published list. Still, the degree of detail of information reported varies notably across EU member states and regions. There is no central

[7] NUTS-LAU definition at Eurostat: https://ec.europa.eu/eurostat/web/nuts/local-administrative-units.

[8] The European Social Fund (ESF) is not considered as information on final beneficiaries (often individuals) is not publicly available. In addition, we do not expect the impact of ESF projects, such as training or labor market measures, to be visible in space in a way like e.g. a (transport) infrastructure project co-financed by the CF or ERDF.

European Commission database collecting project- or beneficiary-level data. Therefore, for the MFF 2007-2013, a dataset of projects co-financed by the ERDF and CF (see Bachtrögler et al. 2019) was updated and extended for the pilot regions investigated by using lists of beneficiaries provided online or after a data request by respective managing authorities. For the MFF 2014-2020, first, a data set of ERDF projects collected in the course of the Stairway to Excellence project run by the European Commission's Joint Research Center (see Bachtrögler, Doussineau & Reschenhofer 2020) was used as a starting point. It includes projects that have been reported by managing authorities in publicly available lists of operations up until June 2019. Second, lists of operations co-funded by the Cohesion Fund in the pilot regions, i.e. in the Czech Republic and Poland, were collected.[9] Information on INTERREG projects co-funded by the ERDF in both programming periods is available from the KEEP database.[10] We have excluded projects initiated after 2019 as they are unlikely to have altered the landscape and therefore cannot be seen in satellite data.

In the course of this project, these data sets of beneficiaries and operations need to be enriched by detailed consideration of geographical location. As the impact of EU funding on changes in land surface or night light emission is to be analyzed, the project's location (e.g. a newly built street) is seen as the variable of main interest. But also the (headquarter) location of the beneficiary can be insightful, especially in case of direct payments to firms or organizations. That is why we consider the postcode of the city or village in which the beneficiary firm or organization is located if the project location is not reported by managing authorities.

For the MFF 2014-2020, Annex XII of the Common Provisions Regulation (EU) No 1303/2013, requests reporting of location of the project itself by "an operation postcode, or another appropriate location indicator". Considering the pilot region analyzed, German and Polish lists of operations report the name of the city (or multiple cities) in which the operation is carried out, whereas Czech lists of operations as well as data on INTERREG projects (co-funded by the ERDF) contain the beneficiary's postcode alone. Therefore, first, postcodes are assigned to German city names using the Geonames database[11], and to Polish city names using the official list of postal address numbers used by the Polish postal service.

For the MFF 2007-2013, the LAU in which the projects are carried out are reported for the Czech Republic. For Poland, as for the MFF 2014-2020, postcodes of projects are assigned to city names reported in Polish lists. For INTERREG projects, postcodes of project partners are available. For Germany, no detailed information is available by beneficiary or by project location but, instead, the *Bundesland* (NUTS-1 region) of the operational program in which a project is carried out. Thus, beneficiary names (in combination with the corresponding NUTS-1 region name) were searched for both in the Google Maps application programming interface (API) and the AMADEUS business database by Bureau van Dijk.[12] Where the beneficiary name was found using both sources but with conflicting information, the correct postcode was verified manually

[9] EU member states with a GNI below 90% of the EU average are eligible for funding by the CF. Therefore, German regions do not receive CF funding.

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

[11] See www.geonames.org.

[12] See https://www.bvdinfo.com/.

(by web search) and, if possible, a unique postcode was assigned. In general, the sample of projects carried out in the pilot region, which is defined at the level of NUTS-2 regions, was selected based on the NUTS-2 regional information reported in original lists of beneficiaries or operations. Concerning the MFF 2007-2013, for Bavaria and Saxony, no NUTS-2 region could be assigned based on information on the operational program. Therefore, the NUTS-3 (and in the following NUTS-2) location was derived from the postcode of the beneficiary using correspondence lists provided by Eurostat. Moreover, for 1.5% of Polish projects there was no NUTS-2 region reported but the NUTS-2 region of the beneficiary, which was considered for the sample selection. INTERREG projects which by definition spread over more than one region (or also member state) form the big exception, as geographical information is available only for individual project partners.[13]

The project database for the ERDF and CF does not include geographic coordinates of the project location. Therefore, localization was accomplished using the postal codes, which have been assigned to each project. In order to combine location information on projects co-funded by the ERDF and the CF with satellite data, the geographical entity of LAUs turned out to be most appropriate. Therefore, a spatial matching of LAUs and their corresponding postal codes was necessary. In this pilot study, spatial locations of the postal codes were acquired from the Geonames project for the three countries.[14] The points were cleaned of geometric and projection errors. By overlaying the spatial data of both LAU and postal codes, each LAU was assigned with the corresponding postal codes. It is thus possible that a) one LAU comprises multiple postal codes and b) a postal code spans multiple LAUs. In this case, respective project amounts are divided by the number of relevant LAU.[15] As a further data cleaning step, information on the correspondence between postcodes (zip codes) and LAU codes from Geonames was verified by checking for the existence of postcodes in official Eurostat lists of correspondence with NUTS-3 regions. Only postcodes included there are considered.

Table 1 shows the share of the EU funding amount reported in the original lists that could be assigned to a LAU and is therefore considered for building the sample in the present analysis (coverage). The fifth column of Table 1 shows the EU co-funding amount considered in this study, and the sixth column compares this amount with official data provided by the European Commission's Directorate-General of Regional and Urban Policy (DG REGIO). The last column makes clear that managing authorities have not yet reported the full set of projects run in the MFF 2014-2020 and that we have excluded projects initiated after 2019 from the analysis. For the MFF 2007-2013, Polish project data almost fully mirrors official payment data, while data on German projects only covers just over half the payments. This is mainly due to the paucity of detail in the list which often exclude the full name of the beneficiary firm or fail in all cases to give any information on beneficiary or project location.

[13] Only INTERREG projects with a lead partner in the Czech Republic, Germany or Poland are considered. In order to avoid double counting, the amount of EU funding for a single INTERREG project, as well as for other projects carried out in more than one city, is divided uniformly by the number of beneficiaries, more precisely, the local administrative units (LAU) in which project partners are located.

[14] Except for Czech data in the MFF 2014-2020 where a LAU code is reported in the original list of operations.

[15] For the analysis of the number of projects, the same project is counted as one in each participating LAU.

Table 1: EU co-funding amounts (at current prices) that could be assigned to LAU in the pilot region, and the comparison of funding amounts considered in our analysis with official data*

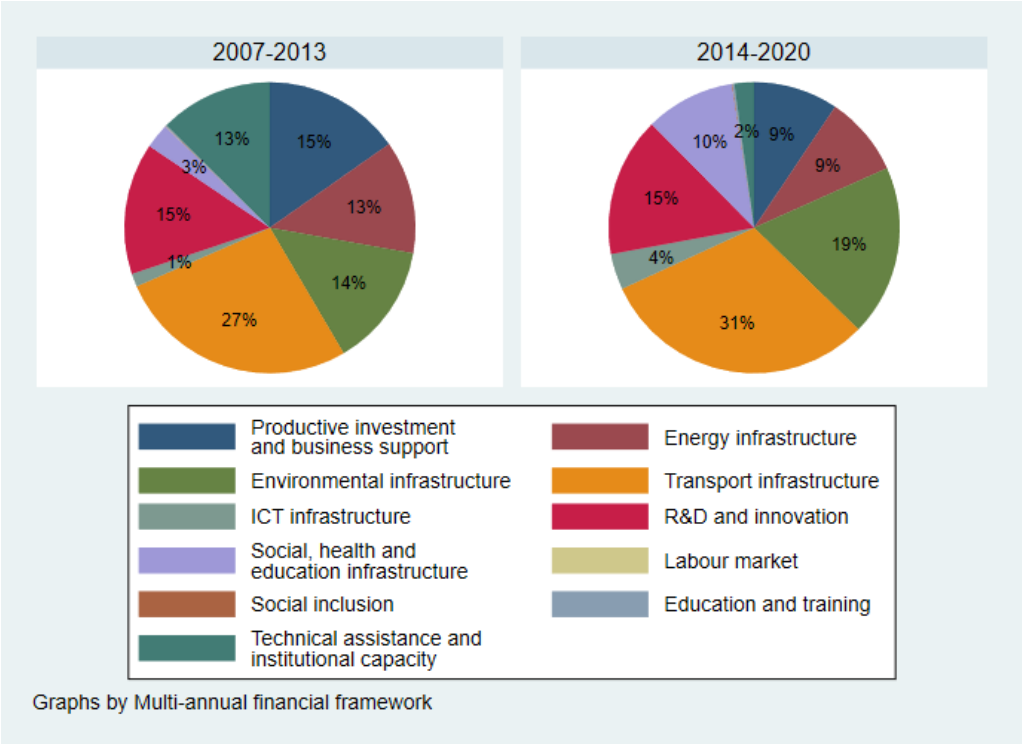
Country	MFF	Fund	Coverage of LAU**	Total EU co-funding amount in pilot regions (in Euro)	Share of EU payments 2007-2013/ allocations to OP 2014-2020***
Czech Republic	2007-2013	ERDF	99.8%	11,801,670,680	117.9%
Czech Republic	2007-2013	CF	99.8%	7,569,510,990	110.8%
Czech Republic	2014-2020	ERDF	100.0%	4,834,330,060	41.9%
Czech Republic	2014-2020	CF	99.9%	3,892,290,260	63.4%
Germany	2007-2013	ERDF	80.0%	3,044,595,710	53.3%
Germany	2014-2020	ERDF	91.4%	2,440,850,180	61.6%
Poland	2007-2013	ERDF	79.9%	8,385,492,700	97.7%
Poland	2007-2013	CF	79.9%	6,459,921,180	98.9%
Poland	2014-2020	ERDF	74.0%	6,696,145,690	23.0%
Poland	2014-2020	CF	44.5%†	2,522,923,100	11.2%
INTERREG	2007-2013	ERDF	88.4%	644,104,240	n.a.
INTERREG	2014-2020	ERDF	95.0%	461,464,840	n.a.

Source: Lists of operations published by managing authorities (see https://ec.europa.eu/regional_policy/en/atlas/beneficiaries and KEEP database.
Notes: *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 in 2014-2020, total eligible expenditure and the (maximum) EU co-financing rate is reported; therefore, we consider the product of these two variables, which actually constitutes a maximum amount funded by the EU, as the ERDF co-funding amount. For German projects in 2007-2013, only the (paid-out) sum of 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. ** Share of the EU co-funding amount among projects that could be assigned to a LAU. For German projects, this share is calculated considering the relevant NUTS-1 regions. For the Czech Republic and Poland as well as INTERREG projects, all projects (within these countries) are considered. *** 2007-2013: ERDF sum includes INTERRREG projects. Comparison with payments reported for pilot regions in the data set of historical regional payments (DG REGIO). Final Czech lists of beneficiaries for 2007-2013 also include projects for which the ERDF funding was not yet paid-out by June 2016. 2014-2020: Comparison with allocations (planned finance published by DG REGIO) to regional or national operational programs part of the 2014-2020 data set. † This is due to a low coverage of project city names reported and therefore of postcodes. With respect to the majority of these missing entries, there is also no regional information reported.

EU structural and cohesion policy supports a broad variety of activities to enhance regional economic growth and competitiveness. While the CF supports network infrastructure building in transport and energy as well as fostering environment protection, the most important project category co-funded by the ERDF is research and innovation, followed by activities to increase the competitiveness of small and medium-sized enterprises. Also, low carbon economy as well as environment protection and resource efficiency are among the top 5 categories of the ERDF in 2014-2020.[16]

A thematic categorization is also available for individual projects co-funded by the ERDF and the CF.[17] Figure 8 shows that almost one third of the funds allocated to the pilot regions is targeted at transport infrastructure projects in both programming periods. This is because both the Czech Republic and Poland devote the bulk of the ERDF and CF funding available to them to network infrastructures in transport and energy.[18] Further important thematic categories are environmental infrastructure as well as R&D and innovation.

Figure 8: Distribution of ERDF and CF co-funding by broad thematic categories



Source: Project data set (see Table 1).

[16]See https://cohesiondata.ec.europa.eu/funds.

[17]For the MFF 2014-2020, a category of intervention (according to Commission Implementing Regulation (EU) No 215/2014) is required to be reported by regulation. For INTERREG projects in both periods, the (first) thematic objective is considered. For the Czech Republic and Poland in 2007-2013, the specific priority of the operational program at which each project is targeted is reported. Based on the different categorical systems, a set of broad categories is defined. These broad categories are, where applicable, assigned to German projects in the MFF 2007-2013 based on project descriptions manually for a learning sample and, in the following, by a Naive Bayes classifier (as well as manual checks).

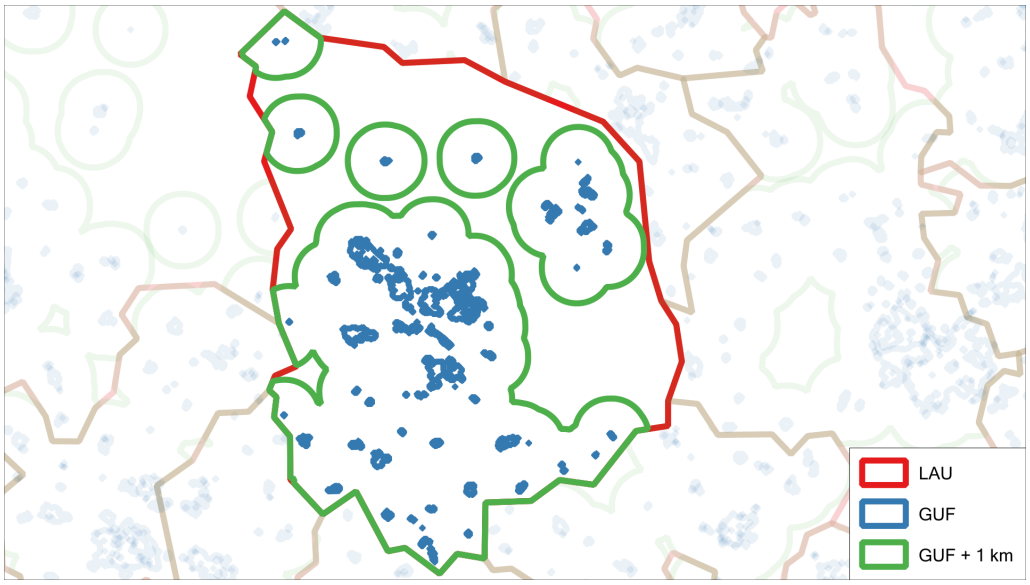
[18]Germany does not spend a notable share in this thematic area. See https://cohesiondata.ec.europa.eu/countries.

3.2 Geographic Data

Bringing together economic, financial and geographic satellite data requires the transition to a unified format. As outlined in Section 3, we use local administrative units (LAU) as the spatial reference frame. Matching the tabulated economic and funding data requires one to spatially aggregate four-dimensional time-series satellite data. That is, satellite data inside a polygon shape is reduced by spatial statistical aggregation, such as the average or median value. However, as the chosen spatial unit might influence the outcome significantly, we test multiple setups. In the following we want to present the theoretical reasoning behind our choice.

Strong night light emitted by thriving economic centers are assumed to be located in close proximity to existing built-up structures. However, administrative units like LAUs often include large parts of non-settlement areas and in some cases might misrepresent the actual morphological settlement area (Taubenböck et al. 2019). This might induce bias into the proxy information derived through spatial aggregation. Therefore, we determine the settlement area inside each LAU using the "Global Urban Footprint" (GUF) (Esch et al. 2013). Developed at DLR, it provides a binary mask of all man-made built-up structures across the globe.

Figure 9: Different geometries within satellite information are spatially aggregated



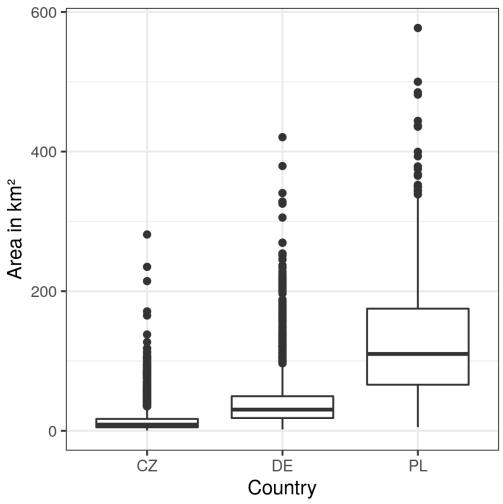
Notes: This map shows the three types of polygon outlines used for spatial statistical aggregation of satellite imagery for an exemplary municipality: the Local Administrative Unit (LAU, red), areas within the Global Urban Footprint (GUF, blue), and areas with a maximum distance of 1 km to GUF areas (GUF + 1 km, green). The latter two incorporate urban areas as well as the urban-rural transition areas.

To further incorporate urban growth and construction outside existing settlements, a buffer zone around all settlement structures was derived. This includes all areas that are no further than 1 km from the closest settlement. Overall, these three geometries were used to aggregate the satellite images (1) administrative area (LAU), (2) settlement area (GUF), (3) buffered settlement area (GUF + 1 km).

Figure 9 shows the three geometries for one exemplary municipality. It can be seen that the entire LAU indicated by the red polygon outline contains quite substantial parts of non-built-up areas. The settlement area inside the LAU is better represented by the GUF products.

It has to be noted that although Eurostat aims to provide a framework of comparable spatial units, LAUs in the different member states vary substantially in size. Figure 10 shows the distribution of LAU sizes in the study region (N = 6571). It indicates that the spatial segmentation is highest in the Czech Republic followed by Germany and Poland. In consequence, the Czech Republic has the highest number of LAUs (N = 3736) whereas Germany and Poland have fewer LAUs in the pilot region (N = 2233 and N = 602, respectively).

Figure 10: Size distribution of LAUs per country in the study region



Notes: The boxplots show the size distribution of all LAUs in the study region per country (CZ = Czech Republic, DE = Germany, PL = Poland). It is apparent that Poland has the largest LAUs with respect to size and the Czech Republic the smallest. Yet, the number of LAUs in the study region for the Czech Republic is 3736, while only 602 LAUs are in the Polish part of the study region. These deviations manifest the differences in the definition of LAUs across the countries of the EU and have to be accounted for in further analyses.

3.2.1 Satellite imagery to proxy economic development

Based on the hypothesis of the project that differences in spatial-local EU funding have an impact on specific local developments, we have developed a catalog of requirements for suitable satellite images. The identified minimum requirements include the following:

1. Provide meaningful features for quantifying human made local environmental change,
2. Availability of data as consistent time series,
3. Full area coverage of the study region,
4. Unrestricted, free data access and open data license.

For this project, we selected different earth observation sensors and data sets. These include data on night light emissions (also abbreviated NLE), land cover and vegetation properties. In the following, the different data sources, data sets and their calibration as well as other preprocessing is outlined in detail.

Nighttime light emissions

In previous studies, night light emissions have been associated with urban and regional economic development (Zhu et al. 2017, Wu & Wang 2019). Such analyses prominently feature data from two different sensors, the "Defense Meteorological Satellite Program Operational Linescan System" (DMSP-OLS) as well as the "Visible Infrared Imaging Radiometer Suite" (VIIRS, Elvidge et al. 2017). Both programs together provide uninterrupted coverage of global night light imagery for the previous three decades.

Although both programs provide imagery of night light emissions, they show significant differences which render them difficult to compare within the scope of this study. First, the sensors operate within different time frames: DMSP-OLS from 1992 to 2013 and VIIRS from 2012 until now. Second, they feature different geometric resolutions: DMSP-OLS images have a pixel size of 30 arcseconds whereas VIIRS show a 4-fold higher resolution of 15 arcseconds. Third, the radiometric and spectral resolutions of the two sensor systems differ. That is, the systems do record different parts of the visible light spectrum and also store them differently in the raw data. In a most recent study, Li et al. (2020) attempt to inter-calibrate and harmonize both DMSP-OLS and VIIRS systems for more continuous night light emission time series data. Despite the effort, however, we found empirical evidence in the application of this project that these data still show a notable difference between the two sensors. Overall, this inevitably leads to the need for separate analyses of the two time series. We thus always use the DMSP data to study funding effects in the MFF 2007-2013 and the VIIRS data for the MFF 2014-2020.

As DMSP-OLS data is not provided as calibrated data sets and VIIRS time series did not exist as yearly average night light emission composites, further preprocessing steps had to be applied to the raw data. In the following these steps are described in detail.

DMSP-OLS preprocessing: Provided by the United States National Centers for Environmental Information – National Oceanic and Atmospheric Administration (NOAA), DMSP-OLS data were acquired as uncalibrated yearly stable light composites. To avoid unreasonable conclusions from systematic biases between different yearly composites, inter-calibration is needed. This was conducted following the approach developed by Li et al. (2013) and Wu & Wang (2019). As a baseline, one image is selected against which all the other images of the time series are calibrated. For that we chose the composite of the year 2001 in accordance with previous studies.

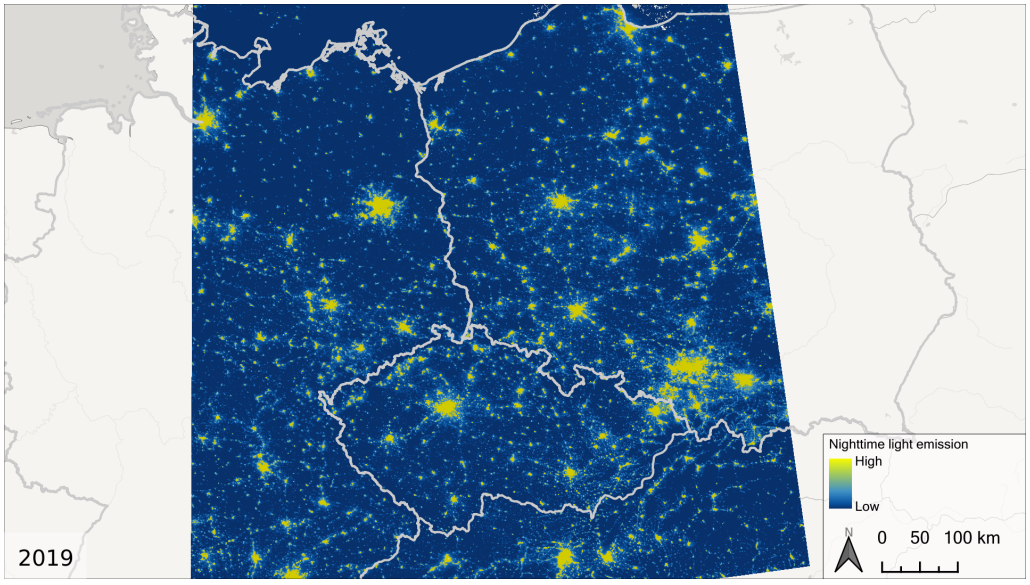
The inter-calibration involves a five-step process based on the assumption that areas with temporally invariant night light emissions, such as remote forest areas, will show stable emission levels over time. These areas of stable emissions are selected automatically in an iterative process in which overlaying pixels of two yearly DMSP-OLS composites are brought together in a linear regression model. Outliers are then iteratively removed by means of standard deviation of the

residuals. By this 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.

VIIRS preprocessing: Since April 2012, monthly composites of VIIRS imagery provide higher spatial resolution and better calibrated data in the spectral domain. However, yearly composites are not available. To provide consistent time series data as for DMSP, yearly composites were aggregated from the freely available monthly composites following the methodology developed by Wu & Wang (2019).

First, utilizing the associated metadata, only monthly composites created from five or more daily images were included. Further outliers with more than 500 $nWcm^{-2}sr^{-1}$ of measured radiance were trimmed. To reduce stray light effects, emissions below 0.5 $nWcm^{-2}sr^{-1}$ were set to zero. Eventually, all monthly composites were aggregated by forming a yearly weighted average. Figure 11 shows an example of a night light mosaic over the study region for the year 2019.

Figure 11: 2019 annual mosaic of VIIRS night light emissions over the pilot region



MODIS Land Cover

In order to monitor the change of the Earth's surface, yearly land cover data are derived from images of the "Moderate Resolution Imaging Spectroradiometer" (MODIS) combined from the Terra and Aqua satellites. Land cover products MCD12Q1.006 are accessible free of charge. From the image data, several yearly land cover products are derived including the IGBP land cover classification (MODIS User Guide). 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 2001 to 2018. They have a spatial resolution of 500 meters. Since some classes did not feature in the study

area and others were semantically similar, we reclassified the original 17 classes into nine more general land cover classes (cf. table 2).

Table 2: Reclassification scheme for IGBP classes used in this study

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

MODIS Vegetation Index

In addition to land cover, information about vegetation properties is derived from the images of the MODIS sensors. In particular, the "Normalized Difference Vegetation Index" (NDVI, Rouse Jr et al. 1974) is a well established measure of vegetative properties. It has also been used in existing studies analyzing urban development and economic growth (Chang et al. 2020, Wu et al. 2020).

The NDVI is an index without unit indicating the abundance and intensity of vegetative areas that scales between -1 and 1. Values below 0 usually indicate unvegetated areas like urban areas, open soil or water. Medium to high values, on the other hand, indicate the abundance of vital vegetation. It is calculated from the reflectance of red and near infrared light:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

where RED is the surface reflectance of visible light in the red spectrum (approx. 0.6-0.7 μm) and NIR corresponds to the surface reflectance of near infrared light (approx. 0.7-1.1 μm, see also the MODIS VI User's Guide) .

The MOD13Q1 product provides a mosaic for each 16-day period since 2000 with a spatial resolution of 250 meters. To account for seasonality and outliers, we reduced the temporal resolution deriving annual average values for the NDVI. Figure 12 shows the 2019 annual NDVI mosaic for the study region.

Figure 12: 2019 annual mosaic of the average vegetation index NDVI over Central Europe

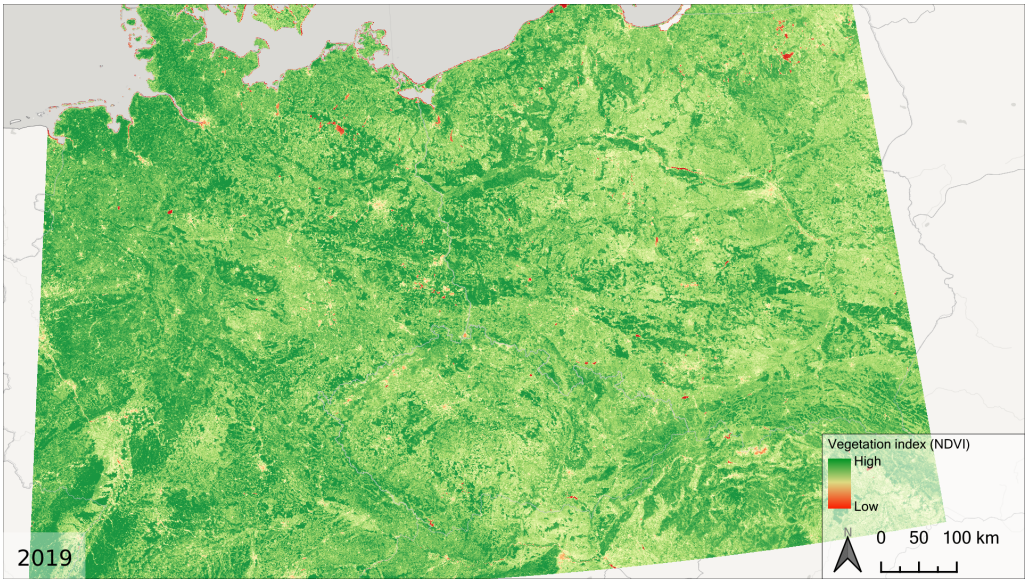
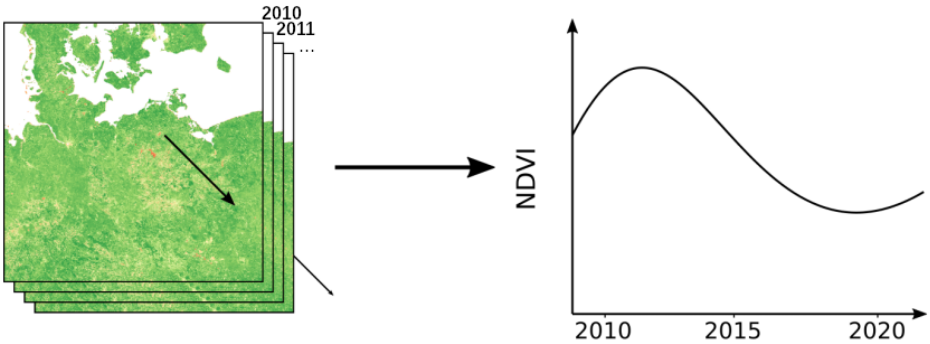


Figure 13 sketches how a series of NDVI images can be compiled to a time series, which in turn can be used to analyze overall trends in the study region.

Figure 13: Sketch of the compilation of multiple images into a time series



3.2.2 Spatial Aggregation of Satellite Imagery for each LAU

The satellite data presented and the products derived as well as the socio-economic and funding data are all available in different spatial units, i.e. pixel-based, LAU as well as NUTS-2 and NUTS-3, respectively. In order to match the data in a spatially unified concept, we (dis)aggregated all data sets to the spatial unit of LAUs. Deriving LAU based statistics for satellite imagery involved compiling zonal statistics for each LAU, i.e. arithmetic aggregates of

the image data within each spatial administrative unit. Zonal statistics allow for an aggregated proxy information aiding evaluation of the changes in each community over time. Further, zonal statistics provide a highly scalable method of processing geodata which perspectively allows the setup to be rolled out to a larger study area.

In this project, the aggregated variables sum, mean, median and standard deviation were chosen. Zonal statistics were calculated for the three geometry sets: administrative unit (LAU), settlement area within each LAU (GUF), and buffered settlement area within each LAU (GUF + 1 km). This is designed to enable subsequent reduction of the effects of imbalance between built and non-built areas within the LAU.

The result of the zonal aggregation is a data set that tabulates observations, in this case all LAUs, and one variable per aggregate from all image data over all years. In total, that accounts for 604 variables for each LAU.

3.3 Regional database

In addition to project and satellite data, we collected regional indicators on the level of the NUTS-3 and NUTS-2 regions from the respective statistical offices.[19] In our analysis, we are mainly interested in recording GDP at the NUTS-3 level, where we validate how well our night light measures can approximate economic growth (see Section 5). In addition, the data from the regional database may serve as additional controls when estimating growth effects and to better understand the economic conditions in different parts of our pilot region. Table A.1 in the Appendix provides summary statistics for all variables that are available at the NUTS-3 level in all three countries. Critically, we have information on GDP, household income and labor market participation. Note though that most variables are not available for the whole period 2007-2019. Especially for 2019 and 2018, many indicators are not available yet. At the NUTS-2 level, even more regional indicators are available. Within the scope of this study, we do not make use of them because we consistently use fixed effects at least at the NUTS-2 level and therefore discard variation that arises from differences between NUTS-2 regions.

[19] For Germany, we retrieved our data from https://www.inkar.de/, for Poland from https://bdl.stat.gov.pl/BDL/start and for the Czech Republic from https://www.czso.cz/csu/czso/home.

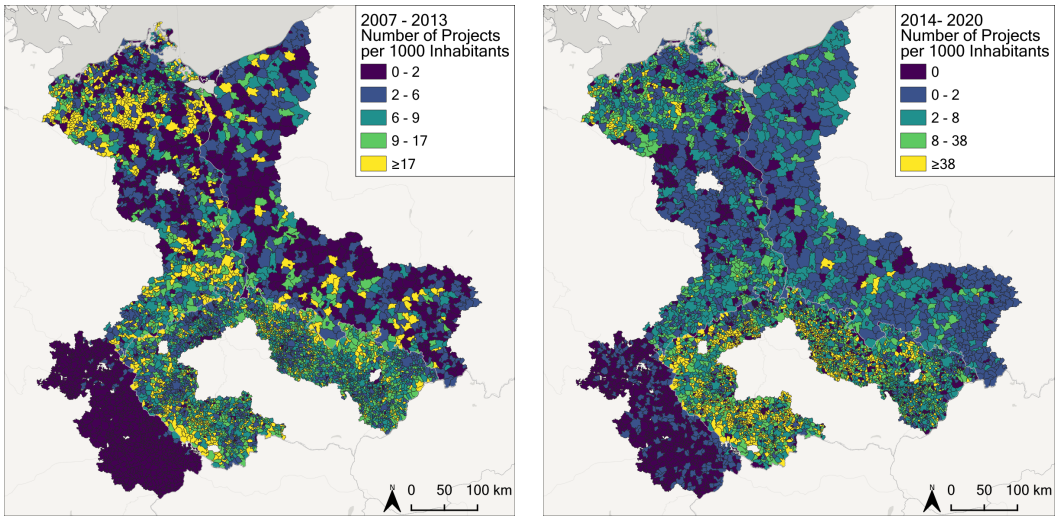
4 The spatial distribution of EU regional funds

While the Directorate-General for Regional and Urban Policy (DG REGIO) of the European Commission provides data on the national (MFF 2014-2020) or regional (MFF 2007-2013) distribution of the ERDF and the CF, our data set of co-funded projects allows for localizing them at the LAU level. To the best of our knowledge, we are the first to document and analyze the distribution of regional funds on such a fine geographical level of aggregation for more than one country. Moreover, our data set makes it possible to differentiate the analysis in terms of thematic categories (see Figure 8) and to check in detail which municipalities in our pilot region invested how much of EU funding - of the ERDF, the CF or both - in which area.

The following figures show the intensity of ERDF and CF funding received in terms of the number of projects carried out in a LAU and the amount of EU funding allocated to each LAU (at current prices, i.e. the nominal values for each year are not adjusted for inflation).[20]

The total number of projects allocated to a LAU in our sample in both programming periods under investigation ranges from zero to almost 7500. However, the distribution of the number of projects among LAUs is highly skewed: The average amounts to 33 projects in one LAU, and half of LAUs in the pilot region carry out 12 or fewer projects in both programming periods. The highest number of projects in our sample is documented for the City of Dresden, Germany, followed by the City of Chemnitz, Germany, and Kobierzyce, Poland.[21]

Figure 14: Number of projects per 1000 inhabitants in MFF 2007-2013 and MFF 2014-2020



(a) MFF 2007-2013 **(b)** MFF 2014-2020

Notes: Colours represent quintiles of the distribution of the indicator. Part of the differences between countries can be explained by the different size of the LAUs.

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

[21] Refer to the Appendix for maps showing the distribution of the absolute number of projects in each and both MFF.

Figure 14 maps the number of projects per 1000 inhabitants in the municipalities in our pilot region. As compared to the other German regions in our sample, which were all classified as less developed or transition regions in the MFFs under consideration, the number of projects in the three more developed Bavarian NUTS-2 regions is throughout relatively low. In the Czech Republic and Poland, where all regions in our sample were classified as less developed in both MFFs, there do not appear to be strong differences between municipalities in different NUTS-2 regions.

Figures A.1 and A.3 in the Appendix show the total number of projects and absolute EU funding amounts per LAU, indicating that there is no direct relationship between the number of projects and the sum of EU funding allocated to a region under study. Having a look at the funding amount per project (aggregated over both MFFs) reveals considerable differences among the countries considered as well as a left-skewed distribution: The mean of the funding amount per project in a LAU in our sample amounts to 169000 Euro, whereas the median is 50000 Euro, and three quarters of LAUs located in our pilot region receive 160214 Euro or less for a single project. While the median funding amount per project is smallest in the German LAUs considered (around 23200 Euro per project), it is more than twice as large among projects in the Czech LAUs under investigation (approximately 51200 Euro per project). The median size of single projects carried out in a Polish LAU in the pilot region over both MFFs corresponds to 174800 Euro. This may be linked to the fact that most funding in Poland is attributed to (large) transportation infrastructure projects but this is also true for Czech regions. Therefore, the funding principles as well as project selection and organization (e.g. allocation of funds for one infrastructure project to one provider or in tranches to more than one provider) appear to differ across member states.[22] Taking the differing size of LAUs into account, Figure 15 maps the EU funding amount allocated to each LAU divided by number of inhabitants.[23] There appears to be a less pronounced gap between the member states and a smoother distribution of funds across all LAUs in our pilot region. However, in line with official data at the national level, the map shows that the level of EU funding in German regions under study is smaller than in the Czech and Polish regions considered. The distribution of the EU funding amount per capita remains highly skewed across the LAUs in our sample (the average value is 3300 Euro per inhabitant; in half of the LAUs considered the total EU funding amount over both periods lies below 1010 Euro per inhabitant).

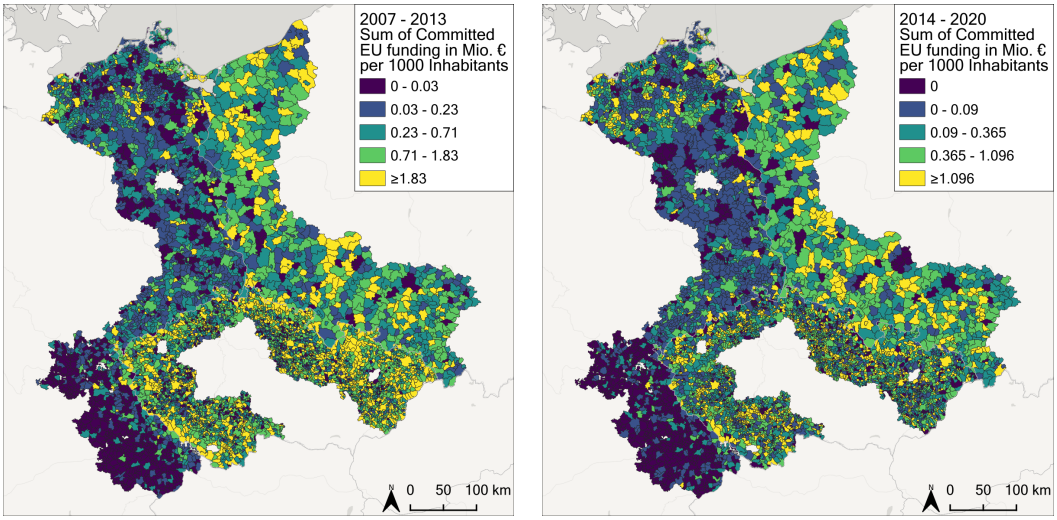
In terms of absolute EU funding amounts, Figure A.3 in the Appendix highlights substantial differences in levels of funding in our pilot region between member states. On the one hand, the relatively high amounts of funding in Poland mirror the fact that Poland is allocated the highest amount of regional funds within the European Union as a whole in the current MFF.[24] On the other hand, the size of LAUs plays a crucial role, as they are significantly larger in terms of area

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

[23] Note that the administrative units of LAU vary in size across countries. While the average LAU in the Czech Republic has less than 1700 inhabitants, LAUs in Poland on average have around 18500 inhabitants.

[24] See https://cohesiondata.ec.europa.eu/funds.

Figure 15: Sum of committed EU funding per 1000 inhabitants



(a) MFF 2007-2013 **(b)** MFF 2014-2020

Notes: Colours represent quintiles of the distribution of the indicator. Part of the differences between countries can be explained by the different size of the LAUs.

and population in Poland than in Germany and, even more so, in the Czech Republic. The three LAUs in receipt of the highest funding levels in our pilot region over the full period of analysis are Ostrava, Czech Republic, followed by the City of Dresden, Germany, and Wrocław, Poland. It is not surprising that all of these are large cities where economic activity is concentrated, pointing to a strong agglomeration effect.

Given that in our sample it is three large cities that profit the most from ERDF and CF funding across the MFFs 2007-2013 and 2014-2020, it is worth exploring the relationship between the amount of funding received and the level of economic activity (before receiving funding) on the one hand, and the difference in funding amounts between rural and urban regions on the other hand. Therefore, we make use of satellite data and test for the correlation of EU funding amounts with initial night light emissions in cities and communes, which is the main variable of interest in our subsequent analysis.

As for population density of LAUs, we investigate both the correlation of funding received with the population of a LAU and with (initial) land cover, i.e. the share of a LAU defined as urban or croplands according to MODIS classification. Table 3 and Table 4 show the results for the total number of projects co-funded in a LAU in MFF 2007-2013 and MFF 2014-2020 in the pilot region, and corresponding EU funding amounts, respectively. We consider country and NUTS-2 fixed effects capturing the overall distribution of the number of projects or project amounts across the region in which each LAU is located (which might be influenced by managing authority).

Table 3: Correlation of number of projects over both multiannual financial frameworks, night light emissions and local characteristics

	(1) No. projects	(2) No. projects	(3) No. projects	(4) No. projects	(5) No. projects
log(NLE_{2007})	0.523***	0.587***	0.365***	0.543***	0.379***
	(102.63)	(129.95)	(52.12)	(115.04)	(53.66)
population			0.229***		0.185***
			(41.33)		(31.02)
share urban$_{2007}$				1.559***	0.972***
				(33.44)	(19.41)
share cropland$_{2007}$				0.024	0.006
				(1.79)	(0.45)
Country FE	Y	Y	Y	Y	Y
NUTS-2 FE		Y	Y	Y	Y
N	85423	85423	85423	85423	85423

Notes: This table reports the estimates of an OLS regression of the number of projects co-financed in both MFFs on the sum of night light emissions in a LAU and land cover at the beginning of the period (2007) as well as population. The inverse hyperbolic sine transformation was applied to population as well as the number of projects. Column (1) includes country fixed effects, columns (2), (3), (4) and (5) NUTS-2 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

The number of projects and even more so the sum of ERDF and CF funds allocated to LAUs is directly linked to the initial level of economic activity, measured in terms of the sum of night light emissions in 2007 (see Section 5). This finding is robust across all specifications (also when considering funding per capita) and suggests that, within our pilot region, higher amounts of funding are allocated to cities and communes enjoying relatively high level of economic activity before receiving the funds. Column (5) of Table 4 indicates that an increase in night light emissions by 1% is associated with a rise in the EU funding amount by around 0.8%. Moreover, Tables 3 and 4 point to a robust positive relationship between the amount of funding and the population. Also, land cover appears to play a role as funding amounts are higher in LAUs with a relatively large built-up area and relatively little cropland.

This finding comes as no surprise, especially for the ERDF which is mainly directed at productive investment and business support as well as R&D and innovation. After all, urban LAUs where many firms are located are likely to profit from agglomeration effects and synergies (thereby producing relatively high levels of nighttime light emissions) and thus attract more funds than regions with relatively little economic activity prior to funding. For the CF, the result appears less intuitive, as its main target is infrastructure projects just as liable to be based within rural areas. Therefore, we run the regression analysis separated for ERDF and CF funding intensity, and can confirm that indeed the link between land cover and CF funds

allocated to a LAU is not statistically significant.

Table 4: Correlation of the sum of EU funding over both MFFs, night light emissions and local characteristics

	(1) EU funding	(2) EU funding	(3) EU funding	(4) EU funding	(5) EU funding
log(NLE_{2007})	1.334***	1.586***	0.863***	1.489***	0.836***
	(88.51)	(112.19)	(39.46)	(100.32)	(37.75)
population			0.743***		0.737***
			(42.95)		(39.46)
share urban$_{2007}$				2.499***	0.161
				(17.06)	(1.03)
share cropland$_{2007}$				-0.444***	-0.515***
				(-10.65)	(-12.44)
Country FE	Y	Y	Y	Y	Y
NUTS-2 FE		Y	Y	Y	Y
N	85423	85423	85423	85423	85423

Notes: This table reports the estimates of an OLS regression of the ERDF and CF co-funding amount in both MFFs on the sum of night light emissions in a LAU and land cover at the beginning of the 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. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

5 Night lights and GDP

In this project we want to evaluate the growth effects of EU funding using night light data. A key requirement for this analysis is that changes in night light emission are actually suited to capture different economic growth paths at the municipality level. Following the seminal paper of Henderson et al. (2012), a number of studies has investigated this relationship and found that night light emissions are generally well-suited to predict GDP. As a result, the use of night light emission probably remains the most popular application of remote sensing data in economics as of today (Donaldson & Storeygard 2016). However, most of the prior evidence is concerned about cross-country differences, whereas we want to leverage the potential of satellite data on a much more granular administrative level. In addition, prior research indicates that the association between night light emission and GDP is stronger in developing countries than in developed economies. This poses the question of how well-suited night light emissions are in our pilot region to detect differences in local economic activity.

We thus assess the strength of the association between economic growth and night light emission in our pilot region. We can do so by aggregating the night light emission from the

municipality level to the NUTS-3 level, where we have information on nominal GDP in our regional database. Table 5 shows the results of a regression of the growth of log(GDP) on the growth of log(NLE) at the NUTS-3 level for both MFFs.[25] In the most simple specification in column (1), we find for the MFF 2007-2013 a coefficient of 0.169, indicating that a 10% increase in the growth rate of night light emission is associated with a 1.69% increase in the growth rate of GDP. In this specification, our nighlight measure is able to capture 16.9% of the variation in GDP growth. Once we additionally control for NUTS-2 fixed effects, we find that the mean night light emission is able to explain 19.4% of the variation in GDP growth between different NUTS-3 regions in the MFF 2007-2013. The estimates are smaller but still highly statistically significant for the MFF 2014-2020. Again, the elasticity is higher once we include NUTS-2 fixed effects. Also for this reason, we consistently employ fixed effects at least at the level of NUTS-2 regions throughout our analysis.

Table 5: Night light emission and GDP growth

	MFF 2007-2013		**MFF 2014-2020**	
	(1)	(2)	(3)	(4)
	ΔGDP	ΔGDP	ΔGDP	ΔGDP
ΔNLE	0.169***	0.194***	0.0720***	0.0977***
	(64.99)	(52.33)	(72.78)	(37.43)
Country FE	Y	Y	Y	Y
NUTS-2 FE	-	Y	-	Y
N	65710	65710	52568	52568
R^2	0.197	0.499	0.196	0.536

Notes: This table displays the results of two separate regressions of the change in log(GDP) on the change in total night light emission for the MFF 2007-2013 (columns (1) and (2)) and the MFF 2014-2020 (columns (3) and (4)). All specifications include country fixed effects, while in columns (2) and (4) NUTS-2 fixed effects are added. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

How do these estimates compare to existing literature? In a similar econometric design, Henderson et al. (2012) regress the growth rate of log(GDP) on the growth rate of mean log(NLE). They find a coefficient of 0.26-0.28 in a country-to-country setting, meaning that the mean night light emission is able to explain about one quarter of the GDP growth variation across countries. Lessmann & Seidel (2017) look at the cross-sectional correlation of GDP and night lights and report a coefficient of 0.18 in a NUTS-1 regional comparison. Our estimates are hence consistent with prior literature, pointing out that night light emission is a good proxy

[25] We follow the literature in taking the log of night light emissions and GDP because both variables have a skewed distribution. In particular, there exist many outliers in the distribution of night light emissions. We thus have a log-log model, where the resulting coefficient can be interpreted as the elasticity of GDP growth with respect to the growth of night light emissions. The growth rate itself is computed as the log difference between the last and the first year of each MFF.

for GDP in also our setting. While our estimates are somewhat smaller than the growth rate elasticities in Henderson et al. (2012), this is not surprising as many authors find a somewhat weaker correlation of GDP and night lights in developed economies (Chen & Nordhaus 2011). Overall, we conclude that night light measurement is well suited to detect differences in local economic activity across NUTS-3 regions in Europe. In the following, we make the (untestable) assumption that this relationship also holds at the LAU level.

6 Convergence between regions

As a last step before evaluating the impact of EU cohesion policy on economic growth, we test for economic convergence in our pilot region. The idea of convergence stems from neoclassical growth theory and hypothesizes that economic conditions between different regional entities will converge over time. In an influential study, Barro & Sala-i Martin (1992) provided empirical evidence that this indeed holds in a cross-country comparison. In the following, a large number of studies has investigated whether convergence has occurred across regions within the EU (e.g. Le Gallo et al. 2003, Marelli 2007). One general result is that there is indeed empirical evidence on convergence among European regions and EU member states. However, economic development within member states has been diverging in recent decades.[26]

While the study of NUTS-2 region convergence is of interest in its own right, convergence at this level was an explicit goal of EU cohesion policy in the MFF 2007-2013. Even more importantly, the existence of convergence has been an obstacle for prior literature in trying to evaluate the economic effects of EU cohesion policy: as at the NUTS-2 level, the majority of funding is explicitly targeted to less developed regions and these also tend to grow stronger even in the absence of EU cohesion policy, this creates a bias in funding estimates if the empirical strategy does not properly account for initial economic conditions. Here, we may falsely attribute higher growth to EU funding if convergence occurs at the municipality level.

We hence ask whether convergence also taking place at the LAU level, for which to date no evidence exists. We can do so by testing whether LAUs with low night light emission at the start of the funding period experienced a higher increase in night light emission than LAUs with an initially high night light emission. We find that this is the case indeed. As reported in Table 6 for the MFF 2007-2013 and in Table 7 for the MFF 2014-2020, LAUs with initially high night light emissions grew significantly less strongly. In the second period, we estimate a coefficient of around -0.2, meaning that a 1% higher level of total night light emission in 2014 is associated with a -0.2% lower growth rate from 2014-2019.

[26] See Mayerhofer et al. (2020) for a detailed discussion of the literature on recent developments and resulting challenges for EU cohesion policy.

Table 6: Convergence, MFF 2007-2013

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE
log(NLE_{2007})	-0.0438***	-0.0530***	-0.0560***
Sum	(-25.63)	(-31.40)	(-32.51)
Country FE	Y	Y	Y
NUTS-2 FE	-	Y	Y
NUTS-3 FE	-	-	Y
N	65710	65710	65710

Notes: This table reports the estimates of a regression of the growth in night light emission in the MFF 2007-2013 on the initial night light emission in 2007. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

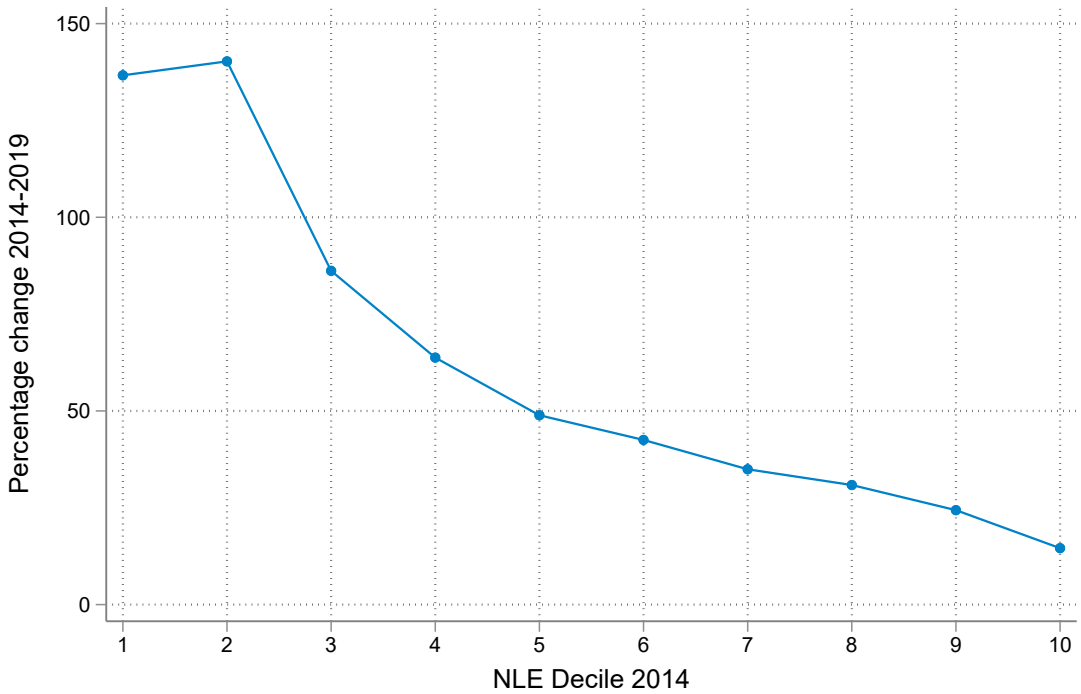
Table 7: Convergence, MFF 2014-2020

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE
log(NLE_{2014})	-0.175***	-0.205***	-0.209***
Sum	(-91.30)	(-103.58)	(-104.80)
Country FE	Y	Y	Y
NUTS-2 FE	-	Y	Y
NUTS-3 FE	-	-	Y
N	52568	52568	52568

Notes: This table reports the estimates of a regression of the growth in night light emission in the MFF 2014-2020 on the initial night light emission in 2014. The growth rate ΔNLE is computed as the log difference between 2019 and 2014. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

As depicted in Figure 16, convergence is especially driven by a high night light emission increase in the two bottom deciles of the distribution. While these municipalities more than doubled night light emission in the period 2014-2019, municipalities in the upper half of the distribution only experienced average growth rates of below 50%. We conclude that when controlling for economic activity at the NUTS-3 level, economic convergence is happening between LAUs in our pilot region. These results highlight that for municipalities as well, it is important to control for initial economic conditions when estimating growth effects.

Figure 16: Mean growth in night light emission by decile, 2014-2019



Notes: This figure shows the mean growth rate of night light emission in the MFF 2014-2020 separately for each decile of the night light emission distribution in 2014. The growth rate is computed as the log difference between 2019 and 2014.

7 Evaluating the funding effects on growth

Finally, we turn to our core question and analyze whether municipalities that received more EU funding than others also experienced higher growth. Again, we consider the MFFs 2007-2013 and 2014-2020 separately throughout our analysis.

7.1 Estimation strategy

To evaluate the effects of EU cohesion policy on growth, one would ideally like to randomly allocate funding across municipalities or regions, so that the funding effect would be independent of any other factors accounting for growth rate differentials. In practice, this is not the case, as for example less developed regions by regulation are allocated higher amounts of funding. Moreover, it is likely that the EU funding amount committed to a municipality depends on regional and local (unobservable) characteristics, such as administrative capacity or the presence of innovative actors to develop projects and successfully apply for funding, as well as further municipality characteristics. As shown in Section 4, funding is more likely to flow into municipalities with high initial night light emission and also varies with the proportion of urban, i.e. built-up, or rural area. To account for this, we control for the initial night light emission

in 2007, the share of urban area, the share of cropland and the population[27] - all at the LAU level. In addition, we use NUTS-2 (NUTS-3) fixed effects to account for any unobserved factors varying across NUTS-2 (NUTS-3) regions. Formally, we thus estimate the following equation

$$\Delta NLE_{i,j} = \beta_0 + \beta_1 funding_{i,j} + \beta_2 X_{i,j} + \phi_j + \varepsilon_{i,j} \tag{2}$$

where for each municipality i in NUTS-2 region j the growth in night light emission ΔNLE in the respective funding period is explained by the funding received, a vector X_i with municipality level controls and a set of NUTS-2 fixed effects ϕ_j. The growth in night light emission is defined as $\Delta NLE = ln(NLE_{t_k}) - ln(NLE_{t_0})$, meaning that we compute it as the log difference between night light emission in the last and the first year of the respective funding period. If funding is uncorrelated to economic conditions once we control for these characteristics, β_1 yields 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. For this reason, our results should be interpreted as correlations and not as causal estimates. In that sense, the results in this Section answer the question whether municipalities that received more funding grew stronger - and not whether the funding *induced* them to grow stronger.

To measure funding, we employ two different variables. First and foremost, we compute the total funding amount that a municipality received in the respective funding period. As the distribution of funds is highly skewed, we employ an inverse hyperbolic sine transformation.[28] Second, we compute the total number of projects each municipality received over the funding period.

7.2 Baseline results

Table 8 shows the results for the first funding period. In column (1), we control for the initial night light emission in 2007 to clean our estimates from convergence effects and employ NUTS-2 fixed effects. Hence, we compare how the growth rate of night light emission varies at the LAU level within a certain NUTS-2 region as a reaction to the funding received, holding fixed the initial night light emission. We estimate a coefficient of 0.00737, meaning that a 1% increase in EU funding is ceteris paribus associated with a 0.007% higher growth in night light emission.[29] This coefficient is statistically highly significant. What does this tell us about the association between funding and GDP growth? Under the assumption that the relation between night light emission and funding at the LAU level is not different from the relation at the NUTS-3 level,

[27] As population at the LAU level is not provided on a regular yearly basis by Eurostat, we use the population for the year 2018.

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

[29] On average, a 1% increase in EU funding amounted to 43,680 Euro in the MFF 2007-2013. For further illustration, Table A.2 in the Appendix shows summary statistics for our main analysis variables like the funding amount and the growth in nightlight emissions per municipality.

we can scale the estimated growth effects in Table 8 with the GDP/NLE correlation as found in column (2) in Table 5. This yields an effect of $0.00737 \times 0.194 = 0.00143$, implying that a 1% increase in funding is associated with 0.0014% higher GDP growth.

In column (2), we additionally control for the respective proportions of urban area and cropland at the start of the funding period as well as for the population of the municipality, as all of these factors are correlated with the probability of receiving funding (see Section 4). The estimate for the funding effect is 0.00633, only marginally smaller and still highly significant. In column (3) and (4) we use NUTS-3 fixed effects instead of NUTS-2 fixed effects. This yields an even stricter set of controls, eliminating all time-invariant differences between NUTS-3 regions. Estimation results barely change.[30]

Table 8: Night light growth and funding amount, MFF 2007-2013

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
funding amount	0.00737***	0.00633***	0.00736***	0.00663***
	(31.37)	(27.20)	(30.71)	(27.99)
log(NLE_{2007})	-0.0662***	-0.0774***	-0.0690***	-0.0834***
	(-61.43)	(-68.84)	(-63.70)	(-73.00)
share urban$_{2007}$		0.0321**		0.00538
		(2.94)		(0.47)
share cropland$_{2007}$		-0.121***		-0.126***
		(-41.63)		(-40.72)
population		0.000000909***		0.00000200***
		(14.56)		(19.59)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	65710	65710	65710	65710

Notes: This table reports the estimates of a regression of the growth in log night light emission in the MFF 2007-2013 on the total funding amount received by each LAU and controls. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

As shown in Table 9, 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

[30]The use of NUTS-3 fixed effects gives extra confidence to our estimates because we exclude confounding factors at an even more fine-grained administrative level. However, we loose a few observations in the estimation of the growth effect, as some LAUs also constitute a NUTS-3 region. For example, the German cities of Dresden and Leipzig form own NUTS-3 regions. Due to this small sample selection, we do not focus on one single preferred specification but consistently report estimates for all four specifications.

the main regressor instead of the total funding amount. For example, the estimates in column (4) imply that having one additional project per municipality is associated with a 0.014% higher growth rate in night light emission. This translates into a 0.0027% higher growth rate of GDP. While these estimates are still significant at conventional levels, the coefficients are estimated with less precision, as we do not differentiate between large and small projects in these specifications. In the following, we therefore focus on the total funding amount as our main treatment variable.

Table 9: Night light growth and number of projects, MFF 2007-2013

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
number of projects	0.000171***	0.0000461**	0.000285***	0.000137***
	(12.61)	(2.68)	(15.44)	(6.79)
log(NLE_{2007})	-0.0557***	-0.0671***	-0.0592***	-0.0729***
	(-54.56)	(-63.04)	(-57.84)	(-67.34)
share urban$_{2007}$		0.0542***		0.0317**
		(4.93)		(2.75)
share cropland$_{2007}$		-0.127***		-0.131***
		(-43.73)		(-41.95)
population		0.000000791***		0.00000169***
		(9.99)		(15.13)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	65710	65710	65710	65710

Notes: This table reports the estimates of a regression of the growth in log night light emission in the MFF 2007-2013 on the total number of projects funded in each LAU and controls. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

Next, we turn to evaluate funding effects in the MFF 2014-2020. Based on the same regression framework, Table 10 reports results for the time frame 2014-2019. Again, the coefficient for the funding amount is positive and highly significant, ranging from 0.0105 to 0.0116. This means that receiving 1% more EU funding is ceteris paribus associated with a 0.01% higher growth in night light emission. This translates to approximately 0.001% higher GDP growth in the MFF 2014-2020. The corresponding results for the number of projects in the MFF 2014-2020 are reported in Table A.3 in the Appendix.

Table 10: Night light growth and funding amount, MFF 2014-2020

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
funding amount	0.0116***	0.0107***	0.0115***	0.0105***
	(21.62)	(19.82)	(21.09)	(19.36)
log(NLE_{2014})	-0.212***	-0.221***	-0.216***	-0.226***
	(-146.84)	(-140.88)	(-147.92)	(-142.15)
share urban$_{2014}$		-0.0539		-0.189***
		(-1.61)		(-5.34)
share cropland$_{2014}$		-0.0913***		-0.101***
		(-10.74)		(-11.06)
population		0.00000373***		0.00000695***
		(20.40)		(23.15)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	52568	52568	52568	52568

Notes: This table reports the estimates of a regression of the growth in log night light emission in the MFF 2014-2020 the total funding amount received by each LAU and controls. The growth rate ΔNLE is computed as the log difference between 2019 and 2014. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

7.3 Robustness of baseline results

To assess the sensitivity of our baseline results with respect to the model specification, we re-estimate equation 2 with two different ways of measuring the funding amount. In Table 11, we apply the log instead of the IHS transformation. We thereby drop all LAUs which received no funding at all and only consider the intensive margin of the funding effect.[31] The estimated coefficients are larger now, pointing out the importance of accounting for the treatment intensity and not only the number of projects.

Table 12 repeats this analysis without any transformation of the funding amount. We thus estimate a log-level model. In these specifications where we do nothing to mitigate the effect of outliers, the association between night light growth and funding is now substantially smaller and less significant. However, the sign of all coefficients remains unchanged.

[31] This is because log(0) is undefined. The intensive margin effect reports the effect of receiving one percent more funding given that the LAU receives any funding.

Table 11: Results for the log of funding, MFF 2007-2013

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
funding amount	0.0165***	0.0150***	0.0165***	0.0153***
	(37.37)	(34.24)	(37.22)	(34.69)
log(NLE_{2007})	-0.0705***	-0.0807***	-0.0722***	-0.0852***
	(-57.86)	(-64.32)	(-59.27)	(-67.13)
share urban$_{2007}$		0.00191		-0.0207
		(0.18)		(-1.82)
share cropland$_{2007}$		-0.119***		-0.122***
		(-40.15)		(-38.40)
population		0.000000772***		0.00000174***
		(12.74)		(17.24)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	56950	56950	56950	56950

Notes: This table reports the estimates of a regression of the growth in log night light emission in the MFF 2007-2013 on the total funding amount received by each LAU and controls. Other than in Table 8, we apply the log transformation instead of the IHS transformation to the funding amount. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

7.4 Accounting for spatial spillovers

The estimation approach in this project takes advantage of the spatial disaggregation of our funding data set, leading us to observe funding and outcomes at the granular LAU level. As discussed previously, this strategy eliminates several problems prior literature has been facing. However, on such a fine-grained level of analysis, spatial spillover effects are also more likely to occur. In the example of Myszków in Section 2, the bypass road appears to have brought substantial economic benefits for Myszków itself. In addition, though, it is likely that adjacent municipalities profited from the road, as it cut commuting times for their inhabitants. Such spillover effects do not always have to be positive: Imagine the EU funding 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 13 re-estimates our baseline results from Table 8 when additionally controlling for funding received by neighboring LAUs. To do so, we define a variable that stores the total funding amount received by all LAUs that share a direct border with the LAU under consideration. This variable captures a spatial spillover effect. Regardless of the specification used, the coefficient of this variable is positive and statistically significant. This demonstrates that spillover effects are present and on average positive. If this variable fully captures the spillover effect, the total funding effect is then revealed as the sum of both

Table 12: Results for the level of funding, MFF 2007-2013

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
funding amount	0.000634***	0.000281***	0.000870***	0.000336***
	(15.93)	(5.13)	(17.56)	(5.64)
log(NLE_{2007})	-0.0574***	-0.0674***	-0.0607***	-0.0728***
	(-55.45)	(-63.21)	(-58.54)	(-67.31)
share urban$_{2007}$		0.0563***		0.0344**
		(5.12)		(2.98)
share cropland$_{2007}$		-0.127***		-0.130***
		(-43.73)		(-41.88)
population		0.000000620***		0.00000161***
		(7.22)		(13.15)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	65710	65710	65710	65710

Notes: This table reports the estimates of a regression of the growth in log night light emission in the MFF 2007-2013 on the total funding amount received by each LAU and controls. Other than in Table 8, we do not transform the funding amount via the IHS transformation. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

coefficients. For example, the funding effect in specification (2) is 0.00602+0.00280=0.0082. This compares to an estimate of 0.00633 in Table 8. This means that while the more naive estimation in Table 8 may accurately capture the local funding effect for the treated LAU, it will structurally underestimate the total treatment effect in the region. The same results hold true for the MFF 2014-2020 (compare Table A.4 in the Appendix).

The existence of spillover effects is interesting from several aspects. First and foremost, it limits the interest for a given LAU to invest in EU co-funded projects if decision makers are aware that a substantial part of the associated benefits accrues to neighboring municipalities. Seen through the lens of an economist, this is a classic externality problem and may rationalize why the money for these types of projects typically stems from higher administrative levels like the state or the federal government. Furthermore, the size of a spillover effect is informative for the economic integration of a region and the importance of agglomeration effects. One would expect that spillover effects are stronger in regions were firms in related fields of business cluster together and and profit from each other. In such regions, EU funding may be especially desirable as the positive funding shock has a high likelihood to propagate also to firms in neighboring municipalities.

Table 13: Funding effect including spillovers, MFF 2007-2013

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
funding amount	0.00694***	0.00602***	0.00706***	0.00637***
	(29.05)	(25.45)	(29.28)	(26.71)
funding in neighboring LAUs	0.00373***	0.00280***	0.00431***	0.00397***
	(10.04)	(7.64)	(11.09)	(10.34)
log(NLE_{2007})	-0.0683***	-0.0790***	-0.0718***	-0.0861***
	(-62.26)	(-69.09)	(-64.60)	(-73.51)
share urban$_{2007}$		0.0322**		0.000863
		(2.95)		(0.07)
share cropland$_{2007}$		-0.119***		-0.125***
		(-40.92)		(-40.21)
population		0.000000928***		0.00000207***
		(14.86)		(20.23)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	65710	65710	65710	65710

Notes: This table reports the estimates of a regression of the growth in log night light emission in the MFF 2007-2013 on the total funding amount received by each LAU and controls. The growth rate ΔNLE is computed as the log difference between 2013 and 2007. The variable *funding in neighboring LAUs* is computed as the sum of funding received by all neighboring LAUs and indicates the size of spillover effects. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

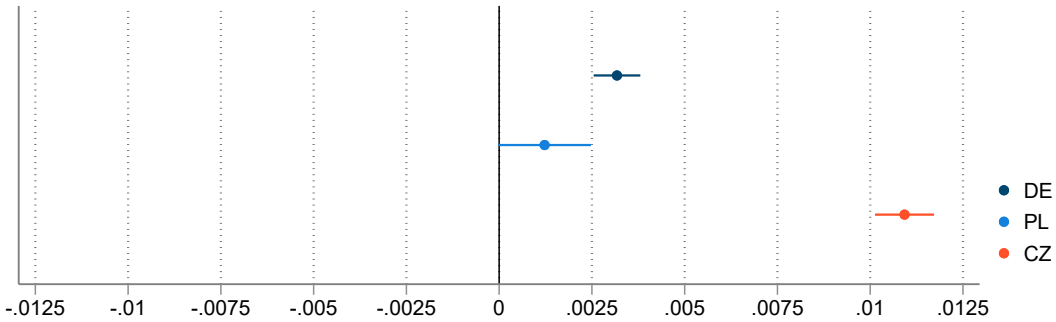
7.5 Heterogeneity

Up until now, we have merely reported aggregate effects of funding. A key strength of our data set however is the possibility to differentiate between types of funds and between funding objectives. In addition, we can check if the growth effect of funding varies across the three countries in the pilot region. In the following, we present evidence for such heterogeneous funding effects. For the sake of brevity, we report these results only for the MFF 2007-2013 in the main part and refer to the Appendix for the MFF 2014-2020.

Heterogeneity by country Figure 17 shows for the MFF 2007-2013 that the association between growth of night light emissions and the funding amount received differs strongly by country. The point estimate for the Czech Republic is three times as high as the one for Germany. In Poland, the funding effect is only marginally significant. The estimate for Poland is also estimated with less precision, as the longer confidence bands indicate. While we can document this heterogeneity descriptively, we are not able to say why these differences arise. On the one hand, the differing size of LAUs may be a statistical reason for country differences, or it may be that there are (further) country-specific factors which render EU funding less

or more effective. On the other hand, it could be that certain type of funds (Table 19) or funding objectives (Table 18) are more effective in inducing growth per se. As there exist large differences across countries regarding type of fund or funding objective, cross-country differences may also be driven by these external factors. More research is needed here to disentangle these effects.

Figure 17: Funding effect by country, MFF 2007-2013

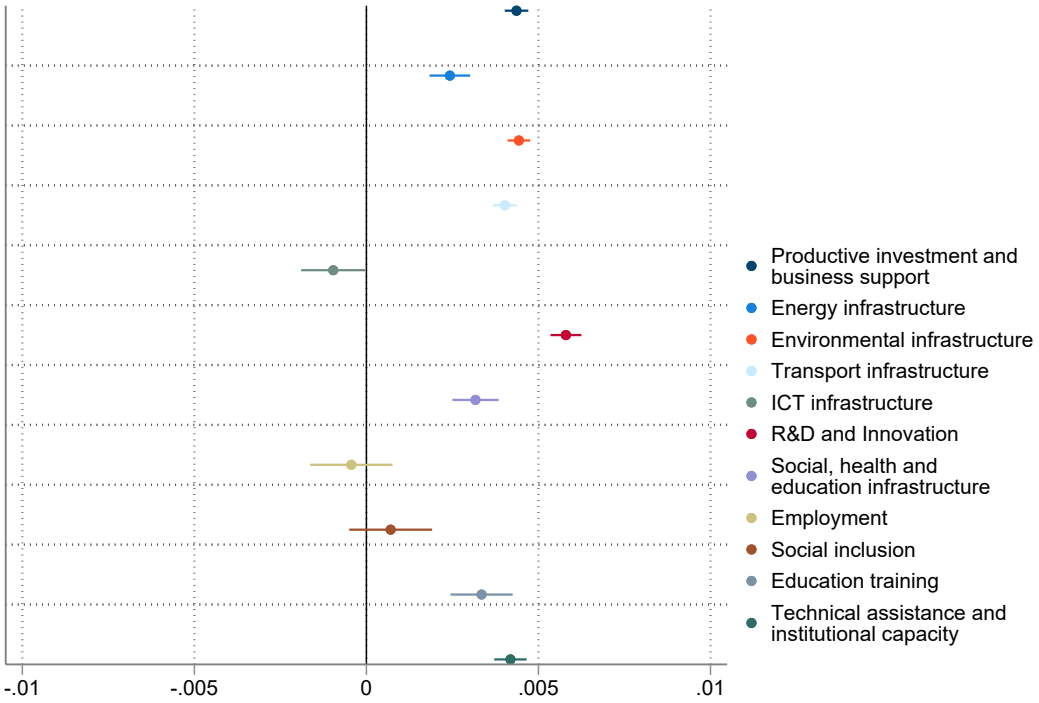


Notes: This figure shows for the LAUs under investigation the coefficient estimate and the corresponding 95% confidence band of a regression of the growth in log night light emission in the MFF 2007-2013 on the total funding amount received as estimated in column (2) in Table 8, separately for Germany (DE), Poland (PL) and the Czech Republic (CZ).

Heterogeneity by funding categories Heterogeneous effects are also likely with respect to the type of projects funded. As described earlier, remote sensing data may vary in their ability to capture the impact of different projects, depending on the funding category. For example, we would expect that funding which directly aims at visible changes in the earth surface like the bulk of infrastructure projects is much easier to spot from space then projects dedicated to foster education or social cohesion. Figure 18 shows that the funding effect indeed varies substantially by project categories. For the categories *ICT Infrastructure*, *Employment* and *Social Inclusion*, the funding effect is insignificant. In contrast, there is a high impact of funding in the categories *Productive Investment and Business Support*, *Environmental Infrastructure* and *Transport Infrastructure*, which all tend to leave visible changes on the ground. The highest coefficient estimate is found for the category *R&D and Innovation*. While this is in line 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 for example transport infrastructure projects.

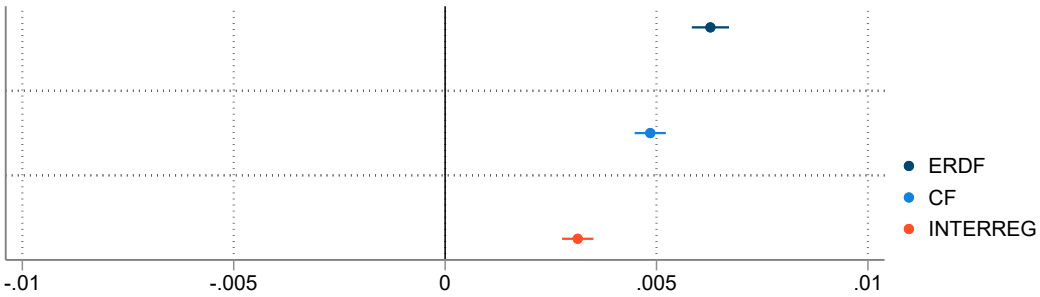
Heterogeneity by type of fund Finally, we compare the funding effect by the type of fund. The allocation of funds in each MFF is a matter of considerable debate in the European Union.

Figure 18: Funding effect by funding objective, MFF 2007-2013



Notes: This figure shows for the LAUs under investigation the coefficient estimate and the corresponding 95% confidence band of a regression of the growth in log night light emission in the MFF 2007-2013 on the total funding amount received as estimated in column (2) in Table 8, separately for the funding objectives as defined by the European commission and described in Section 3.

Figure 19: Funding effect by type of fund, MFF 2007-2013



Notes: This figure shows for the LAUs under investigation the coefficient estimate and the corresponding 95% confidence band of a regression of the growth in log night light emission in the MFF 2007-2013 on the total funding amount received as estimated in column (2) in Table 8, separately by type of fund.

It is therefore worthwhile to investigate if certain types of funds are more effective than others in fostering growth and economic conditions. Figure 19 shows that the funding effect is higher for projects co-funded by the ERDF than projects supported by the CF. This might be a

surprising result as the CF invests above all in transportation and other infrastructure projects. However it should to be noted here that a direct comparison may be biased as Germany does not receive any CF funding. Figure 19 also shows the funding effect of INTERREG projects (co-funded by the ERDF) which appears to be lower than that for ERDF and CF projects. One reason for this could be that many INTERREG initiatives are targeted at more qualitative objectives, such as building networks or cooperations between economic actors, research institutions or public organizations, which are not expected to bring about visible changes in the landscape. Also, the sum of EU funding allocated to INTERREG projects forms only a small part of the total sum of EU funding per LAU (see Figure A.2).

7.6 Alternative outcomes

Besides changes in night light emission, we can also monitor the development of other characteristics recorded from outer space. In the context of EU cohesion policy, it may also be of interest to check for changes in the day-time imagery available to us, most notably the MODIS Vegetation Index (MVI) and the share of a municipality that is built up.

Table 14: Urbanization growth and funding amount, MFF 2007-2013

	(1) $\Delta urban$	(2) $\Delta urban$	(3) $\Delta urban$	(4) $\Delta urban$
funding amount	0.0000140***	0.00000700***	0.0000182***	0.0000106***
	(7.88)	(3.97)	(9.92)	(5.83)
log(NLE_{2007})	0.0000492***	-0.0000300***	0.0000367***	-0.0000299***
	(6.02)	(-3.52)	(4.41)	(-3.40)
share urban$_{2007}$		0.00368***		0.00368***
		(44.39)		(41.52)
share cropland$_{2007}$		-0.0000376		-0.0000790***
		(-1.71)		(-3.32)
population		-2.78e-09***		-4.80e-09***
		(-5.88)		(-6.10)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	65710	65710	65710	65710

Notes: This table reports the estimates of a regression of the growth in the share of urban area in the MFF 2007-2013 on the total funding amount received by each LAU and controls. The growth rate $\Delta urban$ is computed as the absolute difference in the share of urban area between 2013 and 2007. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

Table 14 displays these results for the share of urban area, while the results for the MVI are reported in Table 15. As expected, higher funding is also associated with an increase in urbanization. In some cases like a project that funds the construction of a new street, this relationship is mechanical, as reducing vegetated area directly impacts the MVI. Negative effects of funding on ΔMVI indicate that a loss in vegetative activity can be linked to settlement growth, densification or related construction activities. We find similar results for the MFF 2014-2020 (see Tables A.5 and A.6 in the appendix).

Table 15: MVI growth and funding amount, MFF 2007-2013

	(1) ΔMVI	(2) ΔMVI	(3) ΔMVI	(4) ΔMVI
funding amount	-0.000297***	-0.000224***	-0.000106***	-0.0000745**
	(-10.22)	(-7.87)	(-3.89)	(-2.80)
log(NLE_{2007})	-0.000406**	-0.000427**	-0.000286*	0.000128
	(-3.04)	(-3.11)	(-2.33)	(1.00)
share urban$_{2007}$		0.0330***		0.0276***
		(24.73)		(21.36)
share cropland$_{2007}$		0.0200***		0.0206***
		(56.33)		(59.24)
population		1.15e-08		-1.15e-08
		(1.51)		(-1.01)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	65710	65710	65710	65710

Notes: This table reports the estimates of a regression of the growth in the share of urban area in the MFF 2007-2013 on the total funding amount received by each LAU and controls. The growth rate ΔMVI is computed as the absolute difference in the mean MODIS Vegetation Index (MVI) between 2013 and 2007. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

In contrast to the night light emission, where we know the close association to GDP, the MVI and the degree of urbanisation have no clear analogy to an outcome which is that easy to interpret. To proceed here and really learn from these indicators, one would have to move to a machine learning setting with many indicators, where the researcher can train a supervised learning algorithm to select features that are predictive for a well-defined concept. Here, we conclude that the use of the MVI and the share of urban area add little information to our preferred night light emission measure.

8 Conclusion and Outlook

The new EU budget for 2021-2027 retains cohesion policy as the second largest item. A careful assessment of associated costs and benefits of the EU funding strategy is therefore highly needed. While previous literature, mostly considering NUTS-2 or NUTS-3 regions, points to heterogeneous policy effects on economic development across regions, this study is one of the first to map and assess policy implementation at municipal level in several member states.

This paper has established a novel approach of estimating the effects of EU cohesion policy at a small-scale level. For a pilot region in the border area of Germany, Poland and the Czech Republic, official data on projects co-funded by the ERDF and the CF in the budget periods 2007-2013 and 2014-2020 has been standardized, geolocalized and assigned to the smallest (administrative) spatial unit available; it is then combined with remote sensing data to assess the effect of EU funding at the municipality level. Therefore, compared to previous analyses on the distribution of EU regional funds and the (economic) effects of EU cohesion policy, our analysis has been conducted at a spatially much more granular level.

We have documented the regional distribution of funds across municipalities in our pilot region in terms of thematic categories, funding amounts and the number of projects. The analysis reveals that municipalities with a higher level of economic activity and a larger population are more likely to receive a higher amount of EU funding. In a next step, we have assessed the association between EU funding and economic growth at the municipality level. As regional GDP data is only available down to the NUTS-3 level, we used night light imagery to proxy economic growth. We show that night light emissions are indeed a good predictor for GDP growth at the municipality level. For both funding periods and the pilot region under consideration, we find a positive and statistically significant relationship between EU funding and economic activity as measured by night light emissions. This result is confirmed when accounting for spillover effects generated by higher funding in neighboring municipalities on top.

This pilot study suggests that remote sensing data can be effectively used to capture the small-scale (economic) impacts of place-based policies in a pan-European context. As such, this analysis contributes to the academic literature on the evaluation of EU cohesion policy and informs European and national policy makers. Furthermore, it provides local managing authorities and beneficiaries with insights into the distribution of EU funds to municipalities in other EU member states or regions.

By collecting and processing more data, this analysis could be extended to all EU member states, which would further increase transparency and facilitate future debates on the effective use of funds within European regions. A study covering a wider geographical area would also allow for more convincing ways to pinpoint the causal effect of EU cohesion policy on economic activity, for example by combining municipal data with eligibility thresholds in funding activity or enabling a matching analysis that compares small-scale policy effects in similar regions. Furthermore, additional outcome variables obtained from remote sensing data, such as air quality or high-resolution land cover, could be taken into account for a multi-dimensional assessment of EU cohesion policy on the quality of life in Europe's various regions.

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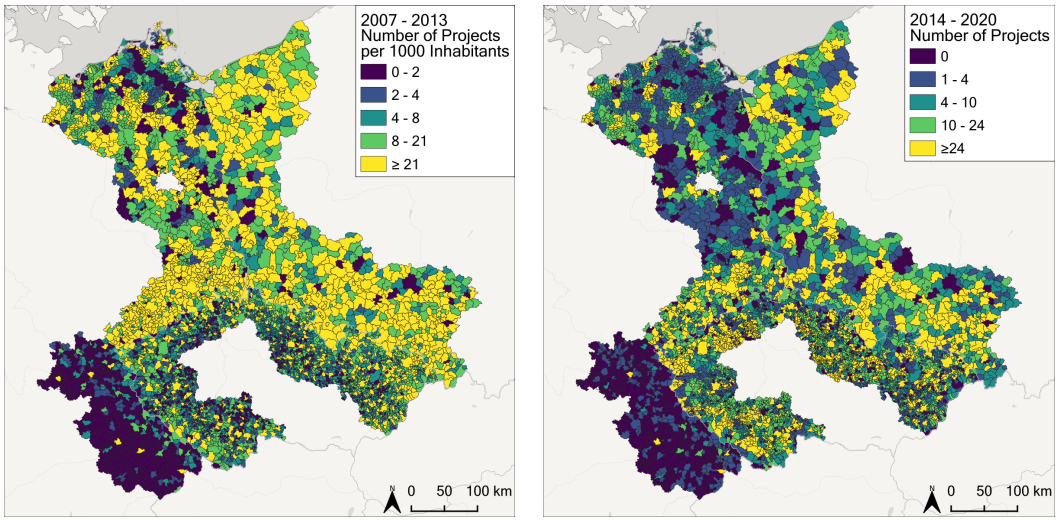
A Appendix

Spatial distribution of EU funding

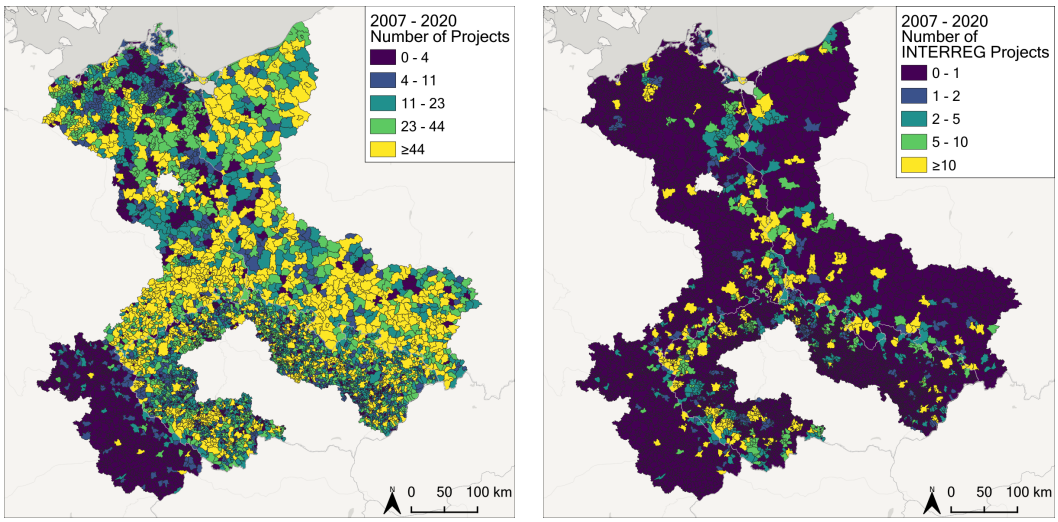
Figure A.1: Number of projects in MFF 2007-2013 and MFF 2014-2020



(a) MFF 2007-2013 **(b)** MFF 2014-2020

Notes: Colours represent quintiles of the distribution of the indicator. Part of the differences between countries can be explained by the different size of the LAUs.

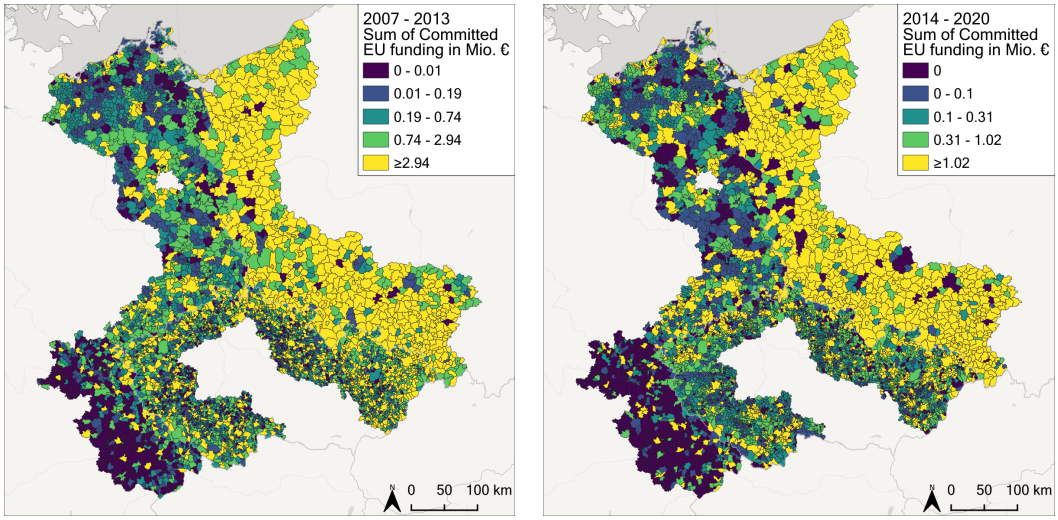
Figure A.2: Total number of projects by LAU and number of INTERREG projects



(a) MFF 2007-2013 + MFF 2014-2020 **(b)** INTERREG

Notes: (a) Colours represent quintiles of the distribution of the indicator. (b) In order to increase visibility, colours are based on a manual classification. Part of the differences between countries can be explained by the different size of the LAUs.

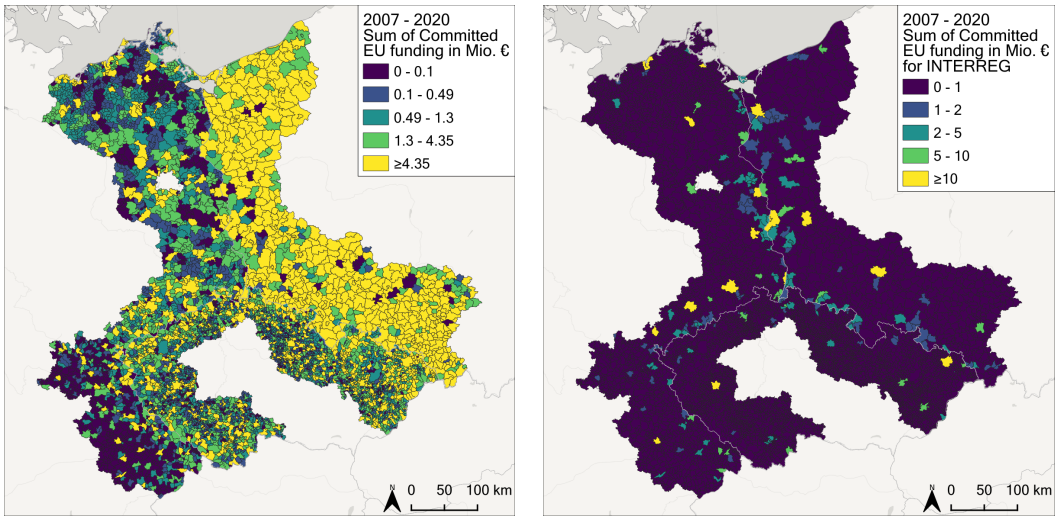
Figure A.3: Sum of committed EU funding in MFF 2007-2013 and MFF 2014-2020



(a) MFF 2007-2013 **(b)** MFF 2014-2020

Notes: Colours represent quintiles of the distribution of the indicator. Part of the differences between countries can be explained by the different size of the LAUs.

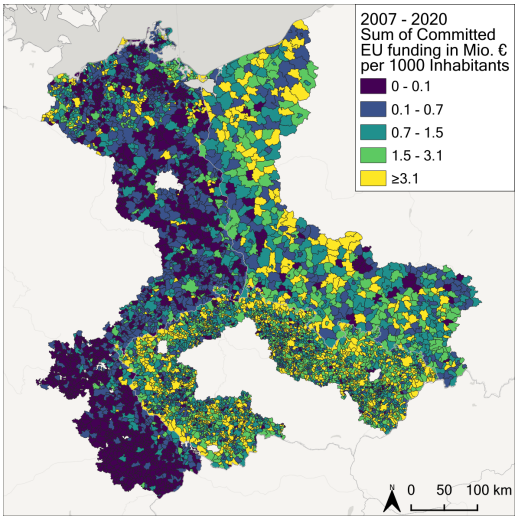
Figure A.4: Sum of committed EU funding for both MFF and INTERREG



(a) MFF 2007-2013 + MFF 2014-2020 **(b)** INTERREG

Notes: (a) Colours represent quintiles of the distribution of the indicator. (b) In order to increase visibility, colours are based on a manual classification. Part of the differences between countries can be explained by the different size of the LAUs.

Figure A.5: Sum of committed EU funding per 1000 inhabitants in MFF 2007-2013 and MFF 2014-2020



Notes: Colours represent quintiles of the distribution of the indicator. Part of the differences between countries can be explained by the different size of the LAUs.

Regional database

Table A.1: Summary statistics for the regional database

	Mean	Median	StdDev	N
GDP	865182.3	4123.8	2722534.0	1132
GDP per capita	24.1	21.9	14.1	1132
Gross value added per worker	43.0	45.7	14.1	1132
New entities created	7.4	7.2	2.1	1142
Number of students	2.7	0.2	4.7	871
Labor Force Rate	78.6	81.4	8.7	911
Employment Rate	76.3	68.2	26.0	911
Number of road accidents	485.0	488.6	247.4	1069
Personal income tax revenues per capita	253.6	240.2	130.1	1142
Corporate income tax revenues per capita	272.7	233.4	294.1	1142
Expenditures for fixed assets	1296.6	537.1	1303.7	323
Land use	16.2	10.6	12.1	710
Share forests	32.4	31.1	10.5	545
Share recreation area	1.9	0.8	2.3	142
Share agricultural land	47.6	49.0	10.9	272
Share water area	2.6	1.7	3.0	272
Unemployment rate	8.3	7.4	4.5	1184
Share unemployed at working age	6.1	5.5	3.1	1184
Share young unemployed am. total unemployed	11.7	10.9	4.2	1119
Share young unemployed am. total population	4.7	3.8	2.8	991
Share long-term unemployed am. all unemployed	31.1	31.2	8.8	1054
Gross monthly wages	1645.0	1923.5	764.4	1144
Net household income per capita	1332.1	1492.0	509.1	901
Share entities with 10-49 workers	68.8	83.3	39.3	849
Share entities with 50-249 workers	15.5	17.4	9.9	849
Share entities with more than 250 workers	2.3	2.2	1.8	849
Share employed in primary sector	2.9	2.9	2.1	710
Share employed in secondary sector	28.9	30.3	9.6	710
Share employed in tertiary sector	68.2	66.2	10.8	710
Waste per capita	3719.0	1708.4	8281.5	1022
Share population at working age	64.2	63.8	3.0	1184
Population	274339.1	191352.0	224377.1	1326

Notes: This table displays summary statistics for all variables in the regional database that are consistently available in at least one year for every NUTS-3 region in the pilot region. Shown are the mean, the median, the standard deviation and the number of non-missing observations. All monetary amounts are displayed in thousands of Euro, except for GDP which is displayed in millions of Euro.

Main Analysis Variables

Table A.2: Summary statistics for the main analysis variables

	Mean	Median	StdDev	Min	Max
MFF 2007-2013					
Number of projects	16.73	3	74.42	0	3189
Funding amount	4368065	149803	24958703	0	8.77e+08
Total night light emission	625.38	245.41	1183.89	2.62	27888.37
Growth night light emission	-0.50%	-1.67%	25.01%	-176.37%	211.97%
MFF 2014-2020					
Number of projects	14.59	5	67.02	0	4124
Funding amount	2312915	112037	17280708	0	5.85e+08
Total light emission	233.12	29.17	1098.08	0.29	44637.45
Growth night light emission	62.30%	44.08%	80.65%	-293.92%	753.83%

Notes: This table displays summary statistics for the number of projects, the funding amount (in Euro), the total night light emission (DMSP-OLS sensor for the MFF 2007-2013, VIIRS sensor for the MFF 2014-2020) and the growth of night light emission per municipality in both MFFs. Total night light emissions are calculated as the sum of the registered night light emissions in the LAU. The emissions are registered as digital numbers (DN, 0 to 63) by the DMSP-OLS sensor and $nWcm^{-2}sr^{-1}$ by VIIRS, respectively. Statistical aggregates *Mean*, *Median*, *StdDev*, *Min* and *Max* are calculated as the summary across all LAUs.

Estimation results for the MFF 2014-2020

Table A.3: Night light growth and number of projects, MFF 2014-2020

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
Number of projects	0.000523***	-0.0000617	0.000952***	0.000367***
	(12.50)	(-1.19)	(12.17)	(4.46)
log(NLE_{2014})	-0.207***	-0.215***	-0.212***	-0.221***
	(-145.47)	(-139.02)	(-146.50)	(-140.50)
share urban$_{2014}$		-0.0549		-0.194***
		(-1.62)		(-5.46)
share cropland$_{2014}$		-0.0939***		-0.102***
		(-11.00)		(-11.06)
population		0.00000414***		0.00000694***
		(18.29)		(21.96)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	52568	52568	52568	52568

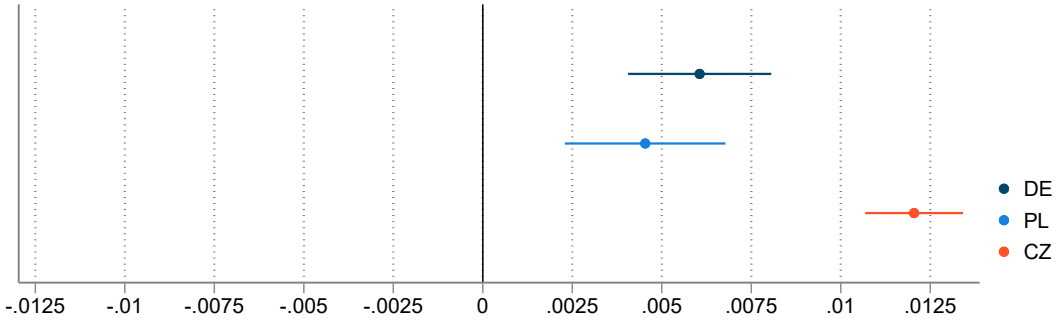
Notes: This table reports the estimates of a regression of the growth in log night light emission in the MFF 2014-2020 on the number of projects received by each LAU and controls. The growth rate ΔNLE is computed as the log difference between 2014 and 2019 (the last year observed in our data). Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

Table A.4: Funding effect including spillovers, MFF 2014-2020

	(1) ΔNLE	(2) ΔNLE	(3) ΔNLE	(4) ΔNLE
funding amount	0.0108***	0.00985***	0.0108***	0.00979***
	(19.97)	(18.26)	(19.79)	(18.08)
funding in neighboring LAUs	0.0145***	0.0140***	0.0182***	0.0179***
	(14.09)	(13.59)	(16.79)	(16.64)
log(NLE_{2014})	-0.215***	-0.224***	-0.221***	-0.231***
	(-147.35)	(-141.51)	(-148.75)	(-143.25)
share urban$_{2014}$		-0.0514		-0.195***
		(-1.54)		(-5.54)
share cropland$_{2014}$		-0.0849***		-0.0972***
		(-10.00)		(-10.64)
population		0.00000373***		0.00000697***
		(20.44)		(23.30)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	52568	52568	52568	52568

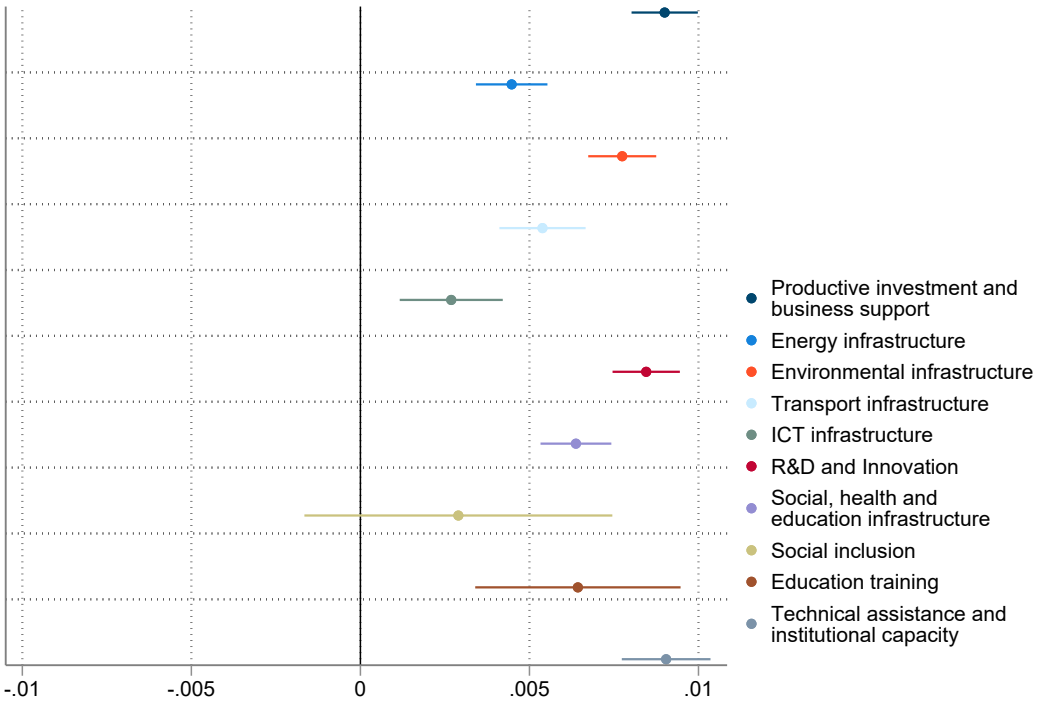
Notes: This table reports the estimates of a regression of the growth in log night light emission in the MFF 2014-2020 on the total funding amount received by each LAU and controls. The growth rate ΔNLE is computed as the log difference between 2019 and 2014. The variable *funding in neighboring LAUs* is computed as the sum of funding received by all neighboring LAUs and indicates the size of spillover effects. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

Figure A.6: Funding effect by country, MFF 2014-2020



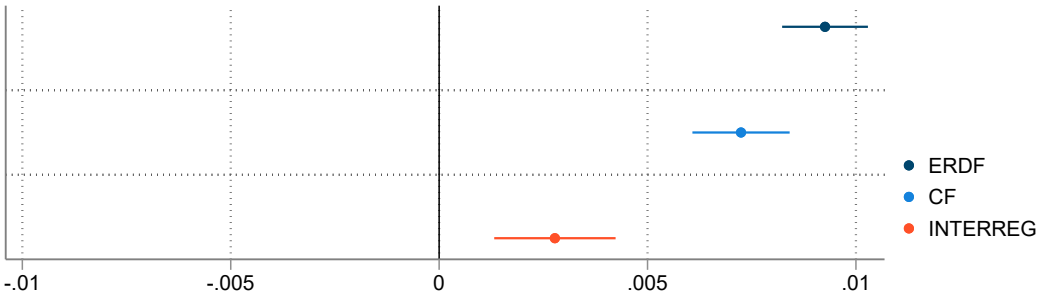
Notes: This figure shows for the LAUs under investigation the coefficient estimate and the corresponding 95% confidence band of a regression of the growth in log night light emission in the MFF 2014-2020 on the total funding amount received as estimated in column (2) in Table 10, separately for Germany (DE), Poland (PL) and the Czech Republic (PL).

Figure A.7: Funding effect by funding objective, MFF 2014-2020



Notes: This figure shows for the LAUs under investigation the coefficient estimate and the corresponding 95% confidence band of a regression of the growth in log night light emission in the MFF 2014-2020 on the total funding amount received as estimated in column (2) in Table 10, separately for the funding objectives as defined by the European commission and described in Section 3.

Figure A.8: Funding effect by type of fund, MFF 2014-2020



Notes: This figure shows for the LAUs under investigation the coefficient estimate and the corresponding 95% confidence band of a regression of the growth in log night light emission in the MFF 2014-2020 on the total funding amount received as estimated in column (2) in Table 10, separately by type of fund.

Table A.5: Urbanization growth and funding amount, MFF 2014-2020

	(1) $\Delta urban$	(2) $\Delta urban$	(3) $\Delta urban$	(4) $\Delta urban$
funding amount	0.00000402**	0.00000190	0.00000153	0.000000474
	(3.19)	(1.53)	(1.20)	(0.38)
log(NLE_{2014})	0.0000757***	0.0000200***	0.0000689***	0.0000188***
	(22.50)	(5.51)	(20.20)	(5.07)
share urban$_{2014}$		0.00260***		0.00261***
		(33.52)		(31.73)
share cropland$_{2014}$		0.0000278		0.0000540*
		(1.41)		(2.54)
population		2.80e-09***		2.07e-09**
		(6.61)		(2.96)
population		-2.78e-09***		-4.80e-09***
		(-5.88)		(-6.10)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	52568	52568	52568	52568

Notes: This table reports the estimates of a regression of the growth in the share of urban area in the MFF 2014-2020 on the total funding amount received by each LAU and controls. The growth rate $\Delta urban$ is computed as the absolute difference in the share of urban area between 2018 and 2014. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

Table A.6: MVI growth and funding amount, MFF 2014-2020

	(1) ΔMVI	(2) ΔMVI	(3) ΔMVI	(4) ΔMVI
funding amount	-0.000219***	-0.000196***	-0.0000817***	-0.0000800***
	(-8.11)	(-7.47)	(-3.37)	(-3.38)
log(NLE_{2014})	0.00125***	0.00118***	0.00104***	0.00102***
	(17.38)	(15.45)	(15.92)	(14.68)
share urban$_{2014}$		0.0195***		0.0181***
		(11.89)		(11.72)
share cropland$_{2014}$		0.0234***		0.0221***
		(56.30)		(55.24)
population		-5.72e-09		-4.43e-08***
		(-0.64)		(-3.38)
NUTS-2 FE	Y	Y	-	-
NUTS-3 FE	-	-	Y	Y
N	65710	65710	65710	65710

Notes: This table reports the estimates of a regression of the growth in the share of urban area in the MFF 2014-2020 on the total funding amount received by each LAU and controls. The growth rate ΔMVI is computed as the absolute difference in the mean MODIS Vegetation Index (MVI) between 2019 and 2014. Columns (1) and (2) include NUTS-2 fixed effects, columns (3) and (4) NUTS-3 fixed effects. t-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. N represents the number of observations.

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