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ORIGINAL ARTICLE

Effects of regional accessibility on productivity: An analysis based on composite indicators

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ABSTRACT

The relationship between transport infrastructure and accessibility has long stood as a central research area in regional and transport economics. Often invoked by governments to justify large public spending on infrastructure, the study of this relationship has led to conflicting arguments on the role that transport plays in productivity. This paper expands the existing body of knowledge by adopting a spatial analysis (with spillover effects) that considers the physical effects of investment in terms of accessibility (using distinct metrics). The authors have used the Portuguese experience at regional level over the last 30 years as a case study. The main conclusions are as follows: i) the choice of transport variables matters when explaining productivity, and more complex accessibility indicators are more correlated with; ii) it is important to account for spill-over effects; and iii) the evidence of granger causality is not widespread but depends on the regions.

KEYWORDS

accessibility; productivity; granger causality; spatial analysis; transport

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1. Introduction

A frequent argument for the investment in transport infrastructure has been its potential impact on economic development and, subsequently, on economic productivity (Graham, 2007a, 2007b; Mačiulis et al., 2009). The transportation network makes it easier for workers to move and for companies to find sources of geographically scattered raw resources. Transport infrastructure has the potential to decrease (temporal) distances, reduce logistical costs, and decrease the friction in trade. On the other hand, it also makes sure that commodities are distributed and that consumers and marketplaces have increased accessibility. Additionally, mobility is a crucial element of competitiveness since it has an impact on logistic costs, population development, and accessibility, all of which have an immediate impact on people's social and economic well-being (López et al., 2008).

Several studies have shown that investments in transportation infrastructure can affect productivity, albeit with different results (or elasticities, from an economic perspective) (see more in Melo, Graham, and Brage-Ardao (2013)). These studies have utilized a variety of methodologies, among which the most common have been production functions, vector auto-regression, and spatial analysis. The studies are made at various levels of granularity (geographical units ranging, generally, between municipalities, regions or countries) to compare or evaluate the effects of transportation infrastructure investments. These studies have been mostly focused on investment or infrastructure stock when characterizing the transport infrastructure. The discussion and computation of investment elasticities for transportation infrastructure have received the majority of attention in the literature on productivity analysis and the effects of transportation systems. This made it possible to calculate the effect that an increase in transportation infrastructure spending would have on productivity.

For instance, Garcia-Mila and McGuire (1992) used the stock of roadway infrastructure to explain per capita output. A similar strategy is used by Aschauer (1988). The authors came to the conclusion that expanding transportation services with more and better quality highway capacity would increase the marginal product of private capital.

This study offers a distinct and novel analysis examining the connection between productivity and accessibility. The basic premise is that accessibility changes, rather than monetary expenditure or the number of infrastructure projects, are a better indicator of how investments in transportation infrastructure would affect productivity.

This research uses Portugal as a case study. The relevance of Portugal as a case study is the fact that Portugal has made a massive investment in its road infrastructure more than doubling its highway system density between 1990 and 2000 (Fernandes et al., 2019; Melo et al., 2022; Rocha et al., 2023). Around 1% of annual GDP is spent (annually) on PPP payments for road infrastructure (Cruz and Sarmento, 2018). The main political motivation for such investment was the potential unlocking of economic growth (Costa et al., 2022). The accessibility impact of such infrastructure is very asymmetrical and different measures of accessibility capture different impacts of such infrastructure development. Therefore, this case study can provide a valuable insight into the role of different accessibility metrics and their relation with productivity. We have added this clarification to the manuscript.

Some authors, like Krugman (1979, 1995), have employed various forms of accessibility in productivity analysis, but accessibility was simulated as a trade flow. Trade flows can help with accessibility, but they are also connected with production, which adds to the challenges. A DEA is also used by Maroto and Zofio (2016) to analyze accessibility, although they use the road network as input instead. However, adding physical accessibility factors rather than only infrastructure stock has become a major concern (of infrastructure growth).

The most common metric in physical measurement investigations has been time travel. In investigations by Graham (2007a, 2007b), Le Néchet et al. (2012), Melo, Graham, et al. (2017), or Rice et al. (2006), this is the case.

This study uses standard transportation measures like physical and temporal distances, infrastructure stock (km of network per type of road), along with more complex indices like overall accessibility, sinuosity, and straight equivalent speed. It makes no a priori assumptions about how to measure the effect of transportation. Our research demonstrates that these composite indices have been useful for regressing production. The relationship between accessibility and production is assessed using a spatial model that considers potential spillover effects resulting from accessibility. The apparent labour productivity is the chosen dependent variable.

Our research is based on three main hypotheses derived from the existing body of knowledge:

- Hip 1: Transport indicators are relevant for the productivity analysis, but their choice can influence the results.
- Hip 2: It is important to account for spatial effects when evaluating the impact of transport on productivity.
- Hip 3: There is evidence of granger causality between accessibility and productivity.

The paper is organized as follows: after this introduction, Section 2 presents the previous literature on the relationship between productivity and accessibility and the derived three research questions; Section 3 discusses the methodological approach for testing each hypothesis; Section 4 presents the results and discusses the main findings; and, finally, Section 5 presents the conclusions, main limitations and future developments.

2. Literature review

2.1. Transport infrastructure and economic development

Over the past several decades, research has focused heavily on the relationship between transportation infrastructure and productivity. The two main reasons are that: (i) it is frequently used as justification for transportation investments (Tcherneva, 2012); and (ii) most nations have been investing in the densification of transportation networks over the past few decades, particularly in road infrastructure and, in some nations, rail infrastructure, which offers valuable case studies (Holl, 2007).

According to Aschauer (1990), public infrastructure can be viewed from a macroeconomic point of view as a contributor to technical development and may therefore have an impact on (increase) economic growth. According to the hypothesis, infrastructure investments made by the government might have a good impact on manufacturing technology. The author created three studies (Aschauer, 1989a, 1989b, 1989c), and they established some relevant empirical implications, arguing that infrastructure spending can have a positive marginal product, is complementary to private investment and can leverage private investment in production capacity. Stepniak and Rosik (2018) assessed the effects of motorway construction in Poland and came to the conclusion that, despite having a positive effect on accessibility generally, road infrastructure has different values in terms of efficiency and equity, and spillover effects vary across Poland depending on the region. According to Holl's (2007) research, infrastructure investments in Spain have a positive impact on economic growth but have uneven distributions of accessibility gains throughout the country. The same author (Holl, 2004) discovered evidence that the construction of motorways in Portugal throughout the 1980s and 1990s increased the economic attractiveness of areas close to the new infrastructure, having an impact on the spatial distribution of business births in most industries.

Assuming the generalized cost function of transportation (see more in Bruzelius (1981); or Button (2010)), transportation expenses have various effects on a company's ability to compete. The most obvious is that consumer traded goods account for a sizeable portion of the total cost of the product, and transportation costs are a component of logistic costs (Cardos and Garcia-Sabater, 2006; Wiengarten et al., 2014). Any enhancement to the transportation system that lowers the cost of transportation would lower the company's costs and boost factor productivity (Holl and Mariotti, 2018).

In some earlier research, public capital was viewed as the total of all public capital investments (transport, energy, environment, public services, etc.). Although it is important to assess the effects of public investment, this prevents us from taking into account the unique contribution of transportation infrastructure.

Some authors have shifted their focus to consider the unique contribution of transportation infrastructure after realizing that it is impossible to assess the contribution of transportation if all investment is included in the "public capital" variable.

In the studies of Pereira and Pereira (2017) and Pereira et al. (2017), differences in transportation investment were taken into account for three different decades. Melo, Graham, and Brage-Ardao (2013) also noted the need to separate transportation investments.

2.2. Accessibility's impact on productivity

According to Hansen (1959), accessibility can be described as "the potential of possibilities for interaction" or "some degree of spatial separation of human activity" (Morrison et al., 1979). Accessibility is often understood as the ability to travel to desired locations and engage in desired activities. Increases in distance, expense, or travel time reduce contact between regions, while accessibility generates socioeconomic benefits for previously remote areas. Infrastructure investment is often a tool that translates into the enhancement of accessibility in regions, as stated by Gutiérrez et al. (2010).

In its turn, this will enable businesses in the same industry (or offering complementary services) to locate in similar regions, a phenomenon called as "agglomeration effects" in the economic literature (see more in Ciccone (2002)). As a result, businesses can collaborate, pool resources, gain from economies of scale, and share knowledge, all of which help them become more competitive. With all the benefits of closeness and its effect on productivity, these "agglomeration effects" will be more pronounced the "easier" it is to relocate (Beeson, 1987; Graham, 2007a, 2007b).

The majority of research in the past has utilized production functions. The Cobb-Douglas functions are the production functions that are utilized the most frequently. One of two methods can be used to incorporate the component related to transportation systems: either by including it as an input factor alongside K and L in the production function, or by using a Hicks-neutral technical change, where Z denotes a number of external factors and T denotes transportation infrastructure.

The Hicks neutrality guarantees that the ratio of capital to labour is unaffected (find out more in Hicks (1966)). A format based on the translog generation function has been utilized in several investigations. The translog function enables numerous inputs into the production function and offers a more flexible approach. For example, Agbelie (2014) used foreign direct investment as a proxy for private capital stock and the number of employable people as a proxy for labour.

The initial estimates of output elasticities have been criticized by "*model misspecifications and spurious relationships*", caused by simultaneity bias and omitted variable bias (covariates not included) (Melo, Graham, and Brage-Ardao, 2013). In fact, most traditional approaches for productivity analysis focus on the impact of the infrastructure stock in a specific region (T_i) on productivity. However, the impacts of the T_i may not be exclusive for that same region and can affect a distinct set of regions that may or may not share boundaries with region *i*. The spatial nature of economic development and, specifically, of the impacts of accessibility on neighbouring regions, will be explorer in Section 2.3.

2.3. Spatial nature of economic development

Economic development often doesn't comply with administrative limits, connecting neighbouring regions through broader effects (Bohman and Nilsson, 2016). Broader effects refer to the idea that the regional impacts could be understated by only considering the direct consequences on one region and neglecting the contributions to other regions (or spill-over effects). Given that the accessibility of one location impacts the accessibility of its neighbouring regions, there are significant spatial linkages to take into account. The development of spatial econometrics (Cliff and Ord, 1981) gave rise to new tools for understanding infrastructure's wider consequences, which gave classic infrastructure literature a fresh viewpoint. Cohen (2010) demonstrated how the absence of a spatially lagged dependent variable might lead to an underestimating of the benefits using a cross-sectional production function model for the US manufacturing sector in 1996.

3. Data and methodology

This section will describe the data and methodology used to address the research hypothesis.

It was required to investigate the impact of all transport indicators on productivity to determine whether our first hypothesis, that transport indicators are relevant for productivity studies, but the choice of such indicators impacts results, is correct. Therefore, the authors used a "drill-down" methodology to first analyze the link at the national level before moving on to the regional level (NUTs III).

There is not a single approach to measuring accessibility that is widely acknowledged; instead, several sets of variables are used depending on the study's goals.

3.1. Accessibility indicators

In order to determine which accessibility metrics are associated with productivity, our research examined various accessibility indicators.

Table 1. Transport variables.

Type of indicator	Description	Unit	Metric	Calculation	Source
Temporal accessibility	Road distance to airports (min) (three different airports)	min	A	Travel time by road from the centroid to the three airports	Transport model
	Railway distance to airports (min) (three different airports)	min	A	Travel time by passenger rail from the centroid to the three airports	Transport model
	Road distance to ports (min) (seven different ports)	min	A	Travel time by freight rail from the centroid to the there ports	Transport model
Physical accessibility	Railway distance to airports (km) (three different airports)	km	A	Physical distance by passenger rail from the centroid to the three airports	Transport model
	Road distance to ports (km) (seven different ports)	km	A	Physical distance by road from the centroid to the three ports	Transport model
	Road distance to airports (km) (three different airports)	km	A	Physical distance by road from the centroid to the three airports	Transport model
Infrastructure stock	Freight railroad extension	km	IS	Physical length of freight rail road	Transport model
	Passenger railroad extension	km	IS	Physical length of passenger rail road	Transport model
	Total road extension	km	IS	Physical length of roads	Transport model
	Principal roads extension	km	IS	Physical length of principal roads	Transport model
	Complementary roads extension	km	IS	Physical length of complementary roads	Transport model
	Other roads extension	km	IS	Physical length of other roads	Transport model
Composite	Straight equivalent speed	km/h	CA	$\boldsymbol{AI_i = \frac{\sum_j \frac{dr_{i,j}}{t_{i,j}} \cdot P_j \cdot e^{-\beta \cdot d_{i,j}}}{\sum_j \cdot P_j \cdot e^{-\beta \cdot d_{i,j}}}}$ AI_i—Infrastructural accessibility *i* (%) P_j—Municipality's inhabitant *j* (hab.) $dr_{i,j}$—Travel straight distance between Municipality *i* and *j* (km) $t_{i,j}$—Travel time between Municipality *i* and *j* (min) $\beta_{i,j}$—Impedance	Transport model based on infrastructures of Portugal index
	Road accessibility	index	CA	$\boldsymbol{AG_i = \sum_j \frac{P_j}{t_{i,j} \cdot S}}$ *AGi*—Municipality's geographical accessibility *i* P_j—Municipality's inhabitant *j* (hab.) $t_{i,j}$—Travel time between Municipality *i* and *j* (min); *S*—Weighting coefficient	Transport model based on infrastructures of Portugal index
	Sinuosity/Winding road index	index	CA	$\boldsymbol{IS_i = \frac{\sum_j \frac{dr_{i,j}}{d_{i,j}} \cdot P_j \cdot e^{-\beta \cdot d_{i,j}}}{\sum_j \cdot P_j \cdot e^{-\beta \cdot d_{i,j}}}}$ IS_i—Sinuosity Index of the Municipality *i* (%) P_j—Municipality's inhabitant *j* (hab.) $dr_{i,j}$—Travel straight distance between Municipality *i* and *j* (km) $d_{i,j}$—Travel road's distance between Municipality *i* and *j* (km) $\beta_{i,j}$—Impedance	Transport model based on infrastructures of Portugal index

Note: A—accessibility; IS—infrastructure stock; CA—Composite index for accessibility.

Table 1 presents the different indicators for transport infrastructure stock and/or accessibility. All the transport variables were provided by the Portuguese transport model developed by Faculty of Engineering of the University of Porto (FEUP). Six variables were considered to gauge accessibility for both road and rail infrastructure: geographic accessibility, sinuosity index, and infrastructure accessibility, measured in time and in kilometers.

The Portuguese infrastructure manager Infraestruturas de Portugal (IP) established these metrics (road and rail). The authors determined each year's and municipality's corresponding value using a GIS-based methodology. This illustrates how accessibility has changed due to the evolution of the physical transportation network. The metrics were combined into the NUTs III spatial scale for the productivity study.

Calculating time travel and time distance was necessary to gather the indicators, and this was done using the Network Analyst toolbox (ArcGIS 10.6). The average travel time to other municipalities was weighted to determine the geographic accessibility (or regions, depending on the geographical unit of the indicator). Population weighting is used to the trip time. The Sinuosity Index weighs the population in each location in addition to the ratio between the straight travel distance (km) and the actual travel distance (km) on the roads. Last but not least, the Infrastructural Accessibility (or comparable speed in a straight line) was determined by the relationship between the distance (km) and travel time (min) between two municipalities, with population weighting done correctly.

To address our initial hypothesis, four different layers of analysis were taken: 1) the first layer would focus on the timeseries relationships between productivity and our transport indicators, first at national level and then at a regional level; 2) a second phase would analyze the spatial dependence of production levels at three different years; this analysis intends to explore the possibility of spillover effects existing across different regions; 3) given that a strong correlation does not necessarily mean that a statistically significant relationship between two time series exists, neither the existence of causality relationship, a cointegration and causality test will be conducted at the regional level; 4) lastly, a model combining the spatial- and time-related features between regions would be developed to assess spillover effects.

3.2. Timeseries relationships

This first phase will analyze the relationship between productivity and our transport variables by conducting a correlation analysis and pairwise regressions. These will be carried out at the national and regional levels and should provide a first glimpse of the underlying relationships.

3.3. Spatial dependences

Choosing the proper econometric strategy is crucial to identifying when to account for geographical effects. Given that numerous examples in the literature emphasize the significance of location in a region's economic development, the authors investigated if the areas' locations on Portuguese territory would affect their apparent labour productivity (Porter, 2000). However, a spatial analysis is required to demonstrate the spatial dependence of productivity (Baumont et al., 2000), as applying spatial modelling approaches is pointless if there is no evidence of spatial dependence since there is no interaction between the regions. On the other hand, the spatial model is the optimum strategy if there is spatial correlation. As a result, the authors did a global Moran-I test and used local indicators of spatial association (LISA) to look at regional clusters (Anselin, 1993).

3.4. Time dependences

To assure the existence of a time dependency between variables, a few crucial measures must be taken while modelling time series (Pereira and Pereira, 2015). Since many models are built on the presumption that the statistical characteristics of the process generating the time series do not change over time, the first step would be to confirm the stationarity of the time series.

To evaluate stationarity, the Augmented Dickey-Fuller (ADF) test was applied. Next, verifying the cointegration of time series ensures the statistical strength of their link and the production of accurate findings from regressions (Granger and Newbold, 1974). Lastly, the Granger-causality test was used to verify the causality between timeseries (Granger, 1969). It is vital to note that the traditional justification for infrastructure spending has an underlying causality: improving accessibility through new or better transportation infrastructure will have a favourable economic impact, which will raise productivity. The Granger causality approach will make it possible to determine whether such patterns exist.

3.5. Spillover effects

Using a cross-regression model based on the research of Bazzi et al. (2017), it was possible to separate the effects of surrounding regions' spillovers by "case-by-case" analysis. To select the number neighbouring regions to be considered, both a rook and a queen contiguity matrix were tested; however, given the context, similar results should be expected. The queen contiguity matrix was chosen to identify relevant spatial dependencies. It is noteworthy that the K-nearest neighbour (KNN) was not considered for this stage as the proximity between regions' centroids would already been considered. A thorough distance matrix, updated at each year of the timeseries to measure proximity of location based on road distance (time), has to be taken into consideration.

3.6. Model

A cross-regressive model was developed based on the work of Bazzi et al. (2017) using Ordinary Least Squares since the analysis is based on exogenous regressors (Le Gallo, 2014). The model is defined as follows:

$$y_{it} = \theta_0 + {z'}_{it}\theta_{z'} + \bar{y}_{(i)_t}\theta_1 + \bar{z}_{(i)_t}\theta_{\bar{z}}$$

where:

y_{it} is $n \times 1$ vector of the apparent labour productivity (*prod_apar*) of region i at year t, functioning as our dependent variable, with n being the number of years in our time series analysis;

${z'}_{it}$ is the $n \times 1$ self-transport variable of region i at time t;

$\theta_{z'}$ is the coefficient for the transport variable at region i, and should translate the effects on productivity of increasing variable z' in region i;

$\bar{y}_{(i)_t}$ is the $n \times 1$ spatially weighted average of apparent labour productivity in neighbouring regions at time t. It is obtained by the product of the spatial proximity matrix ($j \times j$) and the apparent productivity in the neighbouring regions, with j being the total number of regions under analysis. In order to obtain the average weighted value of the variable, in the shape of a $n \times 1$ vector, the authors multiply the row of the spatial weighted matrix corresponding to region i by the value of the variable in each region j at a given year t. By doing this multiplication, the authors obtain one value of the final vector to be used in the regression. Since the time distance between regions' centroids is not constant between years, the authors updated it for every new year calculated for vector $n \times 1$. The proximity matrix accounts only for direct neighbours (*Queen* contiguity matrix) of region i. The proximity is then calculated by inverting the square of the distance between the two regions $(\frac{1}{d_{ij}^2})$, and it is then row normalized so that the sum of each row is equal to 1. This way, it is possible to weigh the influence of each neighbouring region j on region i based on its distance for that given year t. The diagonal of this matrix is null, so that self-effects within region i are not accounted for.

θ_1 is the coefficient which should translate how the productivity in region i is affected by the productivity in neighbouring regions;

$\bar{z}_{(i)t}$ is the $n \times 1$ weighted average transport variable value in the neighbouring regions, and it is calculated similarly to $\bar{y}_{(i)t}$.

$\theta_{\bar{z}}$ is the coefficient which should translate how the productivity in region i is affected by the transport variable in neighbouring regions.

θ_0 is a constant term.

Section 4 will present the results and discussion.

4. Results and discussion

4.1. Transportation indicators and productivity

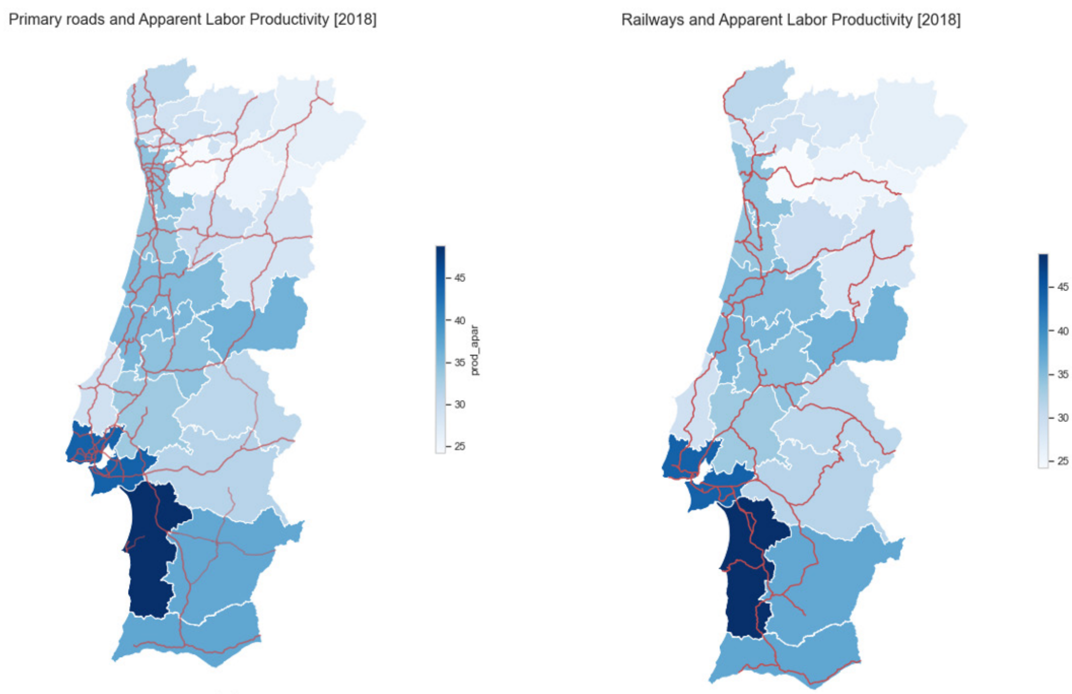
Table 2 presents the results of a pairwise regression of the transportation variables with productivity[1]. The results show that transportation variables have a high correlation with productivity. It is relevant to notice that among the variables with some correlation, there are no related to the rail systems. Instead, road-related variables are dominant, as well as distances to ports and seaports; these latter are probably associated with proximity to the coast (as discussed ahead).

Table 2. Results.

Variable	Correlation	Coefficient	r_sq	n_obs	MAPE
Road accessibility (*acess_viaria*)	0.891	1.459	0.794	17	5.396
Sinuosity (*sinuosidade*)	0.871	8.749	0.759	17	5.27
Straight equivalent speed (*vel_reta*)	0.968	2.529	0.938	17	2.97
Total road extension (*ext_rod_tot*)	0.982	0.007	0.964	19	2.075
Complementary road extension (*ext_rod_ic*)	0.972	0.011	0.945	19	2.65
Other roads extension (*ext_rod_outros*)	0.967	0.146	0.935	19	2.856

By plotting the 2018 geographical distribution of productivity, it is clear that most regions with higher apparent labour productivity are located near the coast (**Figure 1**). This means that there is an apparent strong negative correlation between the distance to seaports and airports, and the apparent labour productivity could be subject to a spatial bias and, therefore, should not be used as a prime indicator of the influence of transportation infrastructure on productivity.

[1] A high Pearson correlation is an indicator of the strong relation between pairs of variables.



(a)

(b)

Figure 1. Spatial distribution of primary roads **(a)** and railway networks **(b)**.

However, the metrics in **Table 2** are independent of being close to a shoreline and, as a result, ought to be a more accurate predictor of how an infrastructure investment might affect productivity. The principal road and railroad networks are overlaid in **Figure 1** to show how both infrastructure networks are moving toward the shore, much as it does with production.

After examining the correlation for the first group of indicators, it is possible to conclude that only the sinuosity index, straight equivalent speed, and road accessibility would exhibit a sufficiently strong (>0.5) correlation to perceived labour productivity (**Table 3**).

There seems to be proof that straight comparable speed and road accessibility both have a definite favourable effect on a region's productivity. However, the relationship between the sinuosity index and values can be less clear in other instances, resulting in near-zero and negative values in specific regions, such as Baixo Alentejo, Alentejo Central, and Alto Minho (**Figure 2**).

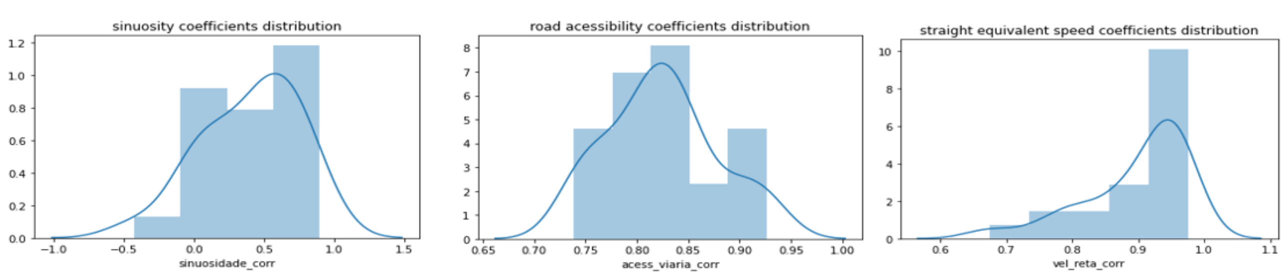


Figure 2. Pearson correlation coefficients distribution.

Table 3. Pearson correlation coefficient between accessibility and apparent labour productivity at regional level.

Region	Road accessibility	Sinuosity	Straight equivalent speed
Alto Minho	0.749	–0.034	0.931
Alto Tâmega	0.925	0.701	0.947
Alentejo Central	0.759	–0.427	0.862
Cávado	0.776	0.334	0.952
Ave	0.821	0.375	0.886
Área Metropolitana do Porto	0.778	0.896	0.976
Tâmega e Sousa	0.897	0.592	0.940
Douro	0.897	0.491	0.963
Terras de Trás-os-Montes	0.926	0.649	0.966
Oeste	0.843	0.774	0.820
Região de Aveiro	0.747	0.146	0.964
Região de Coimbra	0.813	0.688	0.960
Região de Leiria	0.835	0.222	0.934
Viseu Dão Lafões	0.839	0.892	0.960
Beira Baixa	0.856	0.574	0.882
Médio Tejo	0.844	0.432	0.928
Beiras e Serra da Estrela	0.811	0.761	0.875
Área Metropolitana de Lisboa	0.808	0.561	0.802
Alentejo Litoral	0.738	0.046	0.753
Baixo Alentejo	0.799	–0.068	0.792
Lezíria do Tejo	0.855	0.013	0.945
Alto Alentejo	0.819	0.500	0.921
Algarve	0.819	0.124	0.675

According to our second hypothesis, the Alentejo Litoral and Área Metropolitana de Lisboa have the highest values of apparent labour productivity (**Table 4**).

This movement in productivity toward coastal regions implies that location is a critical component to consider when evaluating production. It is noteworthy that spatial autocorrelation influences spatial econometrics models' results; thus, one should test it.

4.2. Testing for spatial effects

The Spatial Autocorrelation (Global Moran's I) tool examines whether the pattern expressed is clustered, scattered, or random by measuring correlation based on both feature positions and feature values simultaneously (Boots and Tiefelsdorf, 2000). It examines the null hypothesis that the values on the map were created at random.

In the event of negative spatial correlation, the geographic occurrences of high and low values would resemble a checkerboard pattern, while in the case of positive spatial correlation, they would resemble a clustered pattern. A case of no geographic correlation, or spatial randomness, would be in the middle, with more heterogeneity than positive spatial autocorrelation but less than negative spatial autocorrelation.

Table 4. Distribution of apparent labour productivity for each region (2008–2018)—higher to lower mean value.

Region	N_obs	Mean	Std.	Min	25%	Median	75%	Max
Alentejo Litoral	11	44.757	4.337	37.799	42.185	42.667	48.581	51.357
Área Metropolitana de Lisboa	11	42.985	0.824	41.518	42.428	43.208	43.595	44.119
Baixo Alentejo	11	33.820	2.561	28.122	33.029	34.374	35.322	37.157
Algarve	11	33.580	2.409	30.243	31.861	33.905	35.197	37.320
Beira Baixa	11	32.860	2.228	28.776	31.794	32.879	34.208	36.085
Região de Leiria	11	32.145	2.407	28.585	30.124	32.895	33.985	35.502
Área Metropolitana do Porto	11	31.911	1.483	30.071	30.736	32.071	32.961	34.274
Região de Coimbra	11	31.743	2.198	28.214	30.559	31.192	33.418	35.208
Região de Aveiro	11	30.627	2.042	27.660	29.143	30.318	32.141	33.913
Médio Tejo	11	30.553	2.520	26.903	28.719	30.849	32.542	34.396
Lezíria do Tejo	11	30.215	1.865	27.479	28.878	30.105	31.226	33.393
Alto Alentejo	11	28.681	1.704	25.622	27.657	28.725	29.998	31.250
Alentejo Central	11	28.652	1.751	26.028	27.670	28.283	29.572	31.654
Alto Minho	11	28.389	2.085	24.144	27.495	28.918	29.781	31.251
Viseu Dão e Lafões	11	27.359	1.624	25.026	25.972	27.401	28.537	29.988
Ave	11	26.621	2.219	22.935	25.038	27.179	28.559	29.318
Alto Tâmega	11	26.062	0.948	24.904	25.253	26.219	26.473	27.894
Cávado	11	25.783	2.179	22.544	23.911	26.291	27.270	29.073
Oeste	11	25.544	2.584	22.008	23.473	25.618	27.852	29.261
Beiras e Serra da Estrela	11	24.541	2.416	21.355	22.979	23.732	26.207	28.483
Terras de Trás-os-Montes	11	23.251	1.585	21.328	22.067	22.882	24.353	26.417
Tâmega e Sousa	11	22.524	1.495	19.625	21.646	23.221	23.649	24.273
Douro	11	21.077	2.320	18.229	19.296	20.452	22.919	25.347

The authors tested the distribution of apparent labour productivity under a Global Moran I, using kernel distance spatial weights with a triangular function, for three distinct moments: 2008, 2012 and 2016.

The findings show that the null hypothesis was rejected in all three situations at a 5% significance level, demonstrating that the distribution of productivity across the country is not random and that the location and interaction between areas have a non-negligible effect which should be considered.

Figure 3 demonstrates a positive association between standardized apparent productivity and spatial latency. This trend is related to positive spatial autocorrelation: similar values tend to cluster together. As a result, the overall trend is for high values to be near other high values and low values to be near other low values. However, this does not imply that this is the only occurrence in the dataset: there may be instances when low ones surround high values and vice versa (geographic outliers).

Looking into the basic pattern of the data in terms of how clustered comparable values are, the easiest way would be to say they are positively linked and, as a result, clustered over space. As a result, the authors investigated where productivity clusters might exist on Portuguese territory. Local Indicators of Spatial Autocorrelation (LISA) (Anselin, 1993) were used to analyze these clusters.

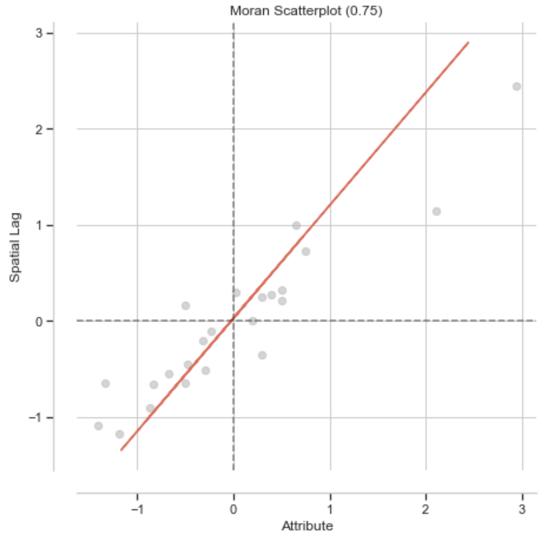


Figure 3. Moran scatterplot.

The Moran scatterplot is divided into four quadrants: i) high values surrounded by other high value areas (HH); ii) high values surrounded by low value regions (HL); iii) low values surrounded by other low value regions (LL); and iv) low values surrounded by high value regions (LL) (LH).

The LH and HL quadrants represent the association of dissimilar values, whereas the HH and LL quadrants represent the association of comparable values (**Figure 4**).

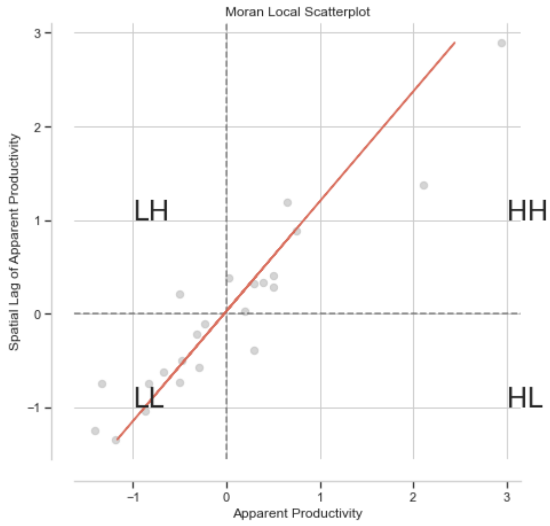


Figure 4. Moran scatterplot.

The goal is to find circumstances where the comparison between an observation's value and the average of its neighbours is either more similar (HH, LL) or more dissimilar (HL, LH) than would be expected from randomness. The process for doing so is identical to the one used in the Global Moran's I, but it is applied to each observation in this case[2].

Most regions are in the HH or LL quadrants, resulting in a global positive value for the Moran

[2] Therefore, there are as many statistics as original observations.

I statistic. As a result, there is evidence of spatial productivity clusters. To ensure consistency, the authors used kernel weights with triangle functions.

Two distinct clusters have been found based on the value of local statistics: one consists of two regions in the HH quadrant (in red), and the other is composed of five regions in the LL quadrant (in yellow) (**Figure 5**).

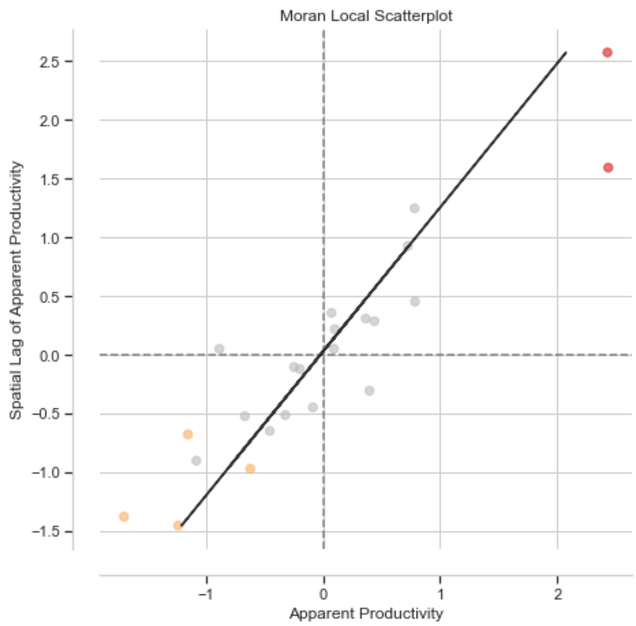


Figure 5. Moran local scatterplot (2012).

By plotting the clusters geographically, it is noticeable that the high-value cluster is composed of the Lisbon Metropolitan Area (LMA) and Alentejo Litoral (**Figure 6**). These findings show that productivity in these locations is positively affected by productivity in neighbouring regions, establishing a cluster of high productivity. On the other end of the scale, the regions of Alto Tâmega, Douro, Tâmega e Sousa, and Ave form a Low-Low (LL) cluster. This suggests that the relatively low values in these regions are caused partly by low values in the surrounding areas, resulting in a LL cluster. Because regions within the same productivity cluster tend to act similarly, positive (or negative) outcomes may be reinforced.

The location of these clusters has shifted slightly over the three years of investigation, with the region of Terras de Trás-os-Montes being added to the first cluster in 2008. The trend appears to have removed LMA from the southern cluster, which could be explained by lower labour productivity in neighbouring regions.

Each region is surrounded on average by four neighbours (**Figure 7**). Therefore, the number of neighbours considered was increased by defining the kernel weights triangular function to four, testing the stability of the results.

The results reveal that having a larger range of nearest neighbours resulted in a larger dimension on clusters. In the south, there is a larger cluster composed of the areas of LMA, Alentejo Litoral and Baixo Alentejo, with a widening to the regions of Algarve and Lezíria do Tejo in 2018 (**Figure 8**). Because of its lower apparent labour productivity, the region of Alentejo Central stands apart.

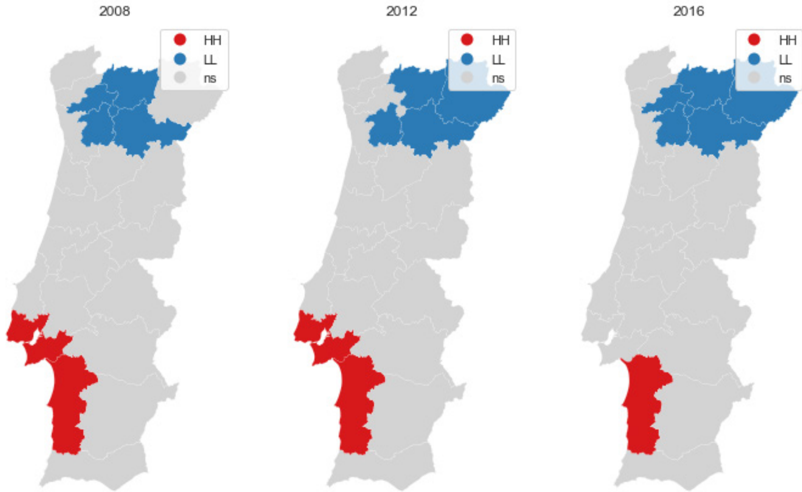


Figure 6. LISA indicators for the years of 2008, 2012 and 2018. Kernel distance weights with triangular function and considering 2 nearest neighbours.

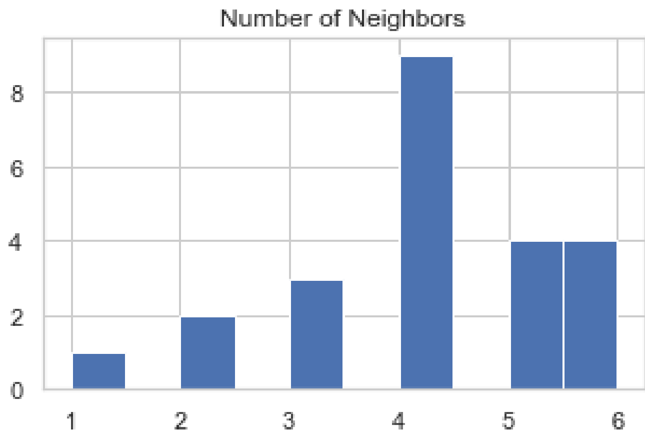


Figure 7. Histogram for number of neighbours.

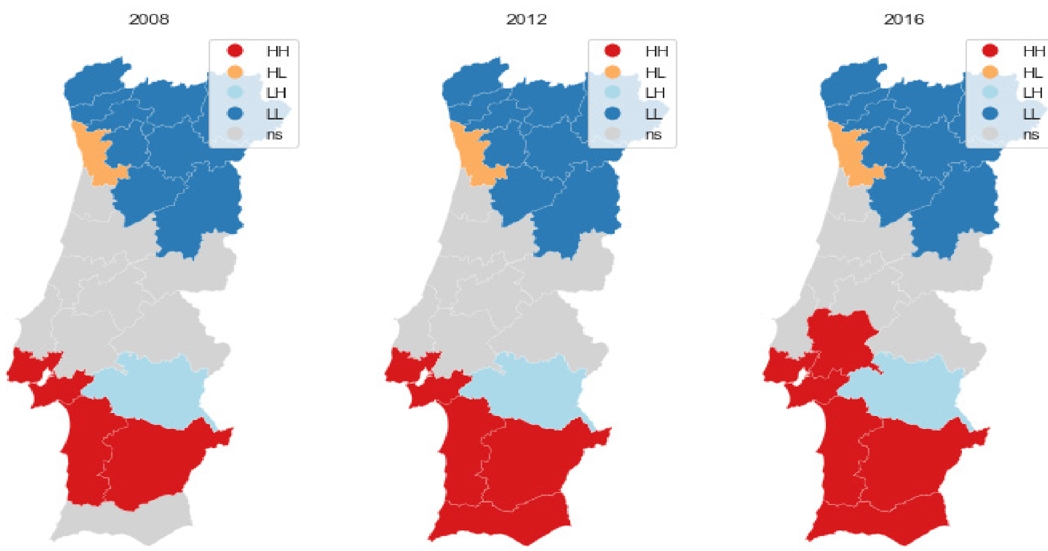


Figure 8. SA indicators for the years of 2008, 2012 and 2018. Kernel distance weights with triangular function and considering 4 nearest neighbours.

The regions of Alto Minho, Cávado, Ave, Alto Tâmega, Tâmega e Sousa, Douro, Terras de Trás--os-Montes, Viseu Do e Lafes, and Beiras e Serra da Estrela make up the northern cluster. Zona Metropolitana do Porto stands out due to its increased apparent labour productivity.

Based on the collected data, the authors may propose that spillover effects will have a greater impact within each cluster. To analyze these effects, a model isolating spatial dynamics' effect in each location is required (NUTIII). The first step was to examine how productivity changed in each region compared to its neighbours. These findings would then be utilized to create a spatial proximity matrix to weigh the impact of each neighbour on spillover effects. However, one should note that these spillover effects may decay linearly or quadratically with distance. This should be addressed has it has implications on how the proximity matrix should be constructed. With this purpose, the authors analyzed the convergence of values for:

$$\frac{\Delta prod\_apar_{ij}}{d_{ij}}$$

where $\Delta prod\_apar_{ij}$ is the difference in apparent labour productivity between a given region i and its neighbouring regions j, given a distance d_{ij} between their centroids. The coefficient of variance (CoV) was used as a measure of "convergence" for the value: the smaller the CoV, the better the region is described by the linear/quadratic relationship. The authors assumed that if the value of *quadratic_reg* converged to a single number, the relationship between *prod_apar* in a given region and its neighbours would be quadratic. On the other hand, if the value of *linear_reg* converges to a single number, the relationship between *prod_apar* in a given region and its neighbours are linear. Therefore, NUTs with smaller CoV for *linear_reg* are better defined by a linear relationship and hence the proximity matrix should be calculated as $\frac{1}{d_{ij}}$, while NUTs with smaller CoV for *quadratic_reg* are better described by a quadratic relationship and thus the proximity matrix should be calculated as $\frac{1}{d_{ij}^2}$.

According to the findings, the following regions tend to have a linear decline in production influence with distance: Cávado, Tâmega e Sousa, Trás-os-Montes, Região de Leiria, Beira-Baixa, Médio Tejo, Serra da Estrela, LMA, Alentejo Litoral, and Lezíria do Tejo. On the other hand, the productivity influence appears to diminish quadratically with distance in the following regions: Ave, Alto Tâmega, Douro, Algarve, Oeste, Aveiro, Coimbra, Viseu Dão e Lafões, Baixo Alentejo, Alto Alentejo, and Alentejo Central are all municipalities in Portugal. Because Alto Minho has only one bordering region, both decay functions are valid.

4.3. Timeseries analysis

4.3.1. Testing for cointegration

Evaluating the variables for cointegration is critical before modelling a time series. If they are cointegrated, it is demonstrated that they have a substantial statistical link and will thus produce non-spurious findings. The authors employed the Engle-Granger cointegration test, as Pereira and Pereira (2015) did. The results (**Table 5**) demonstrate that the null hypothesis may be rejected 69% of the time for sinuosity index, 60% of the time for straight equivalent speed, 39% of the time for road accessibility, 30% for employment, and 56% for investment rate. There is evidence of cointegration between the time series in these circumstances.

Table 5. Engle-Granger cointegration test results.

	Sinuosity		Straight equivalent speed		Road accessibility		Jobs		Total investment rate	
Region	***t*-statistic**	***p*-value**	***t*-statistic**	***p*-value**	***t*-statistic**	***p*-value**	***t*-statistic**	***p*-value**	***t*-statistic**	***p*-value**
Alto Minho	–6.436***	1.76×10^{-7}	–5.168**	7.96×10^{-5}	–4.013*	6.87×10^{-3}	7.701	1.00	–0.301	9.76×10^{-1}
Alto Tâmega	–4.67**	6.36×10^{-4}	0.457	9.92×10^{-1}	–5.686**	7.46×10^{-6}	–2.015	5.20×10^{-1}	–1.763	6.47×10^{-1}
Alentejo Central	–4.431**	1.59×10^{-3}	–4.906**	2.43×10^{-4}	–0.045	9.85×10^{-1}	–0.431	9.69×10^{-1}	–3.592	2.50×10^{-2}
Cávado	–3.076	9.31×10^{-2}	–16.231***	2.91×10^{-28}	–3.368	4.60×10^{-2}	–1.224	8.51×10^{-1}	–6.136***	8.20×10^{-7}
Ave	–4.737**	4.87×10^{-4}	0.144	9.89×10^{-1}	–6.739***	3.52×10^{-8}	–6.347***	2.79×10^{-7}	–6.051***	1.25×10^{-6}
Área Metropoltiana do Porto	–3.361	4.68×10^{-2}	–4.697**	5.70×10^{-4}	–4.148	4.36×10^{-3}	–3.931*	8.96×10^{-3}	–0.672	9.49×10^{-1}
Tâmega e Sousa	–24.043***	0.00	–20.817***	0.00	–4.145	4.40×10^{-3}	–5.192**	7.17×10^{-5}	–6.215***	5.48×10^{-7}
Douro	–13.260***	8.30×10^{-24}	–8.609***	8.62×10^{-13}	–5.977***	1.81×10^{-6}	–2.700	1.99×10^{-1}	–3.899	9.93×10^{-3}
Terras de Trás os Montes	–4.984**	1.75×10^{-4}	–4.947***	2.06×10^{-4}	–3.601	2.44×10^{-2}	–14.163***	1.90×10^{-25}	–5.914***	2.48×10^{-6}
Oeste	–4.598**	8.39×10^{-4}	–4.507***	1.19×10^{-3}	–4.015*	6.83×10^{-3}	–2.481	2.87×10^{-1}	–10.925***	1.26×10^{-18}
Região de Aveiro	–4.180*	3.90×10^{-3}	–4.538**	1.06×10^{-3}	–3.933*	8.92×10^{-3}	–8.234***	7.74×10^{-12}	–0.639	9.53×10^{-1}
Região de Coimbra	–0.700	9.47×10^{-1}	–4.677**	6.17×10^{-4}	–5.387**	3.00×10^{-5}	–6.424***	1.87×10^{-7}	–4.910**	2.40×10^{-4}
Região de Leiria	–6.355***	2.67×10^{-7}	–2.822	1.58×10^{-1}	–3.236	6.40×10^{-2}	–6.502***	1.24×10^{-7}	–9.550***	3.42×10^{-15}
Viseu Dão Lafões	–5.193**	7.13×10^{-5}	–1.983	5.37×10^{-1}	–3.594	2.49×10^{-2}	0.731	9.94×10^{-1}	–7.497***	5.38×10^{-10}
Beira Baixa	–6.134***	8.26×10^{-7}	–6.167***	6.99×10^{-7}	–5.820***	3.92×10^{-6}	–2.969	1.18×10^{-1}	–6.110***	9.32×10^{-7}
Médio tejo	–6.748***	3.36×10^{-8}	–3.715*	1.75×10^{-2}	–3.862*	1.12×10^{-2}	–1.324	8.22×10^{-1}	–0.281	9.77×10^{-1}
Beiras e Serra da Estrela	–2.715	1.94×10^{-1}	–2.625	2.28×10^{-1}	–4.121*	4.77×10^{-3}	7.983	1.00	–1.651	6.99×10^{-1}
Área Metropolitana de Lisboa	–13.863***	6.36×10^{-25}	–13.64***	1.61×10^{-24}	–18.014***	1.85×10^{-29}	–3.382	4.43×10^{-2}	–4.585**	8.83×10^{-4}
Alentejo Litoral	–5.917***	2.44×10^{-6}	–3.058	9.69×10^{-2}	–132.813***	0.00	–4.795**	3.84×10^{-4}	–10.869***	1.72×10^{-18}
Baixo Alentejo	–5.442**	2.34×10^{-5}	4.541	1.00	–4.028*	6.54×10^{-3}	22.443	1.00	–2.190	4.29×10^{-1}
Lezíria do Tejo	–2.611	2.32×10^{-1}	0.762	9.94×10^{-1}	0.484	9.93×10^{-1}	–2.510	2.75×10^{-1}	1.519	1.00
Alto Alentejo	–2.27	3.84×10^{-1}	–11.452***	6.97×10^{-20}	–4.760**	4.43×10^{-4}	–3.192	7.12×10^{-2}	–4.031*	6.46×10^{-3}
Algarve	–6.712***	4.08×10^{-8}	–5.282**	4.82×10^{-5}	–5.893***	2.74×10^{-6}	–3.712*	1.77×10^{-2}	–33.618***	0.00

* *p-value < 10%,* ** *p-value < 5%,* *** *p-value < 1%.*

However, it is not possible to reject the null hypothesis in a significant number of situations. As a result, when using a regression, it is prudent to search for statistical soundness as there are false results. Because the distribution of these discoveries does not appear to follow a geographical trend, they must be considered case by case (**Figure 9**).

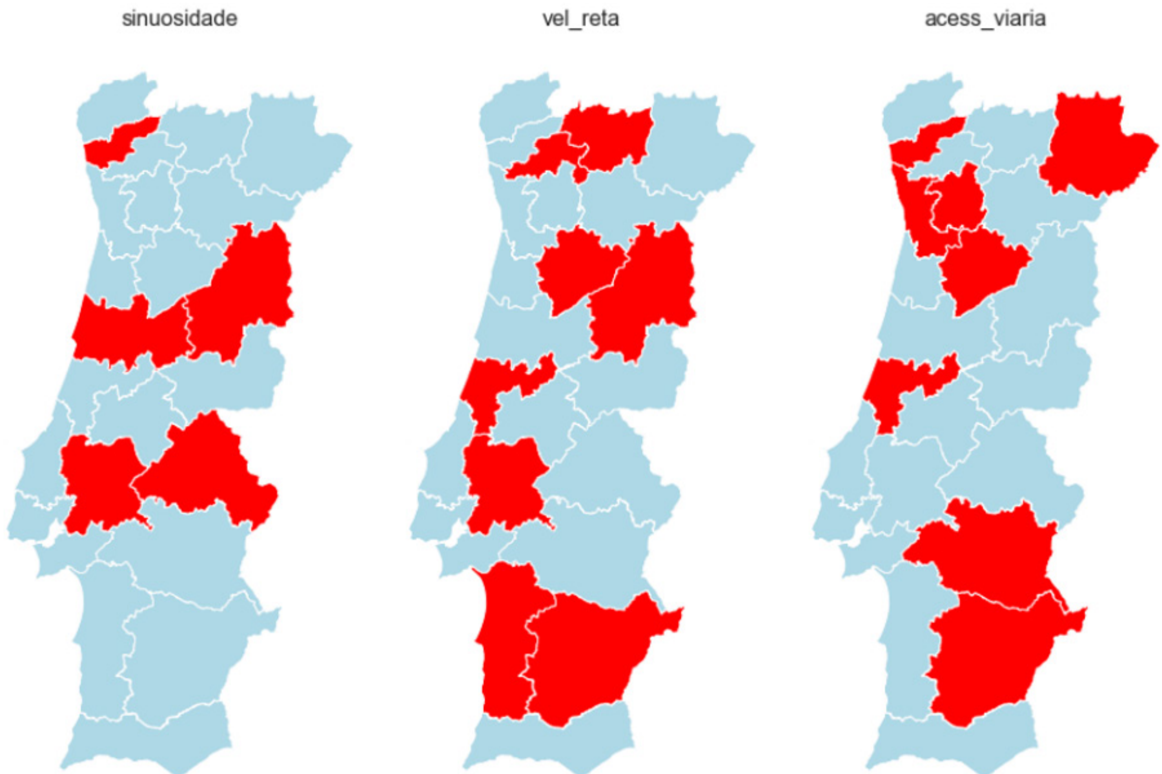


Figure 9. Regions with no rejection for null hypothesis (α = 10%).

4.3.2. Granger causality

The presence of a correlation between accessibility (as measured by various measures) and productivity was demonstrated in the preceding subsections. However, as previously said, correlation does not imply causation. Therefore, using the granger causality technique, it is necessary to look for evidence of causation, i.e., whether improved accessibility leads to increased productivity.

There is evidence of a significant association between certain transport indicators and apparent labour productivity after doing a simple correlation study of national timeseries. However, the specific indications may differ depending on the place under consideration. The following indicators are most suited to explain productivity at the national level:

- Straight Equivalent Speed (*vel_reta*).
- Road accessibility (*acess_viaria*).
- Principal roads extension (*ext_rod_ip*).
- Complementary roads extension (*ext_rod_ic*).
- Total road extension (*ext_rod_tot*).

The first three variables are crucial when modelling national aggregated data for productivity. Straight equivalent speed (*vel_reta*) and road sinuosity (sinuosidade) were found to be superior indicators at the regional level.

When the trend of straight equivalent speed and apparent labour productivity is examined, it is clear that both variables have been increasing since the beginning of the century (**Figure 10**). In addition, both the sinuosity index and road accessibility are trending upward.

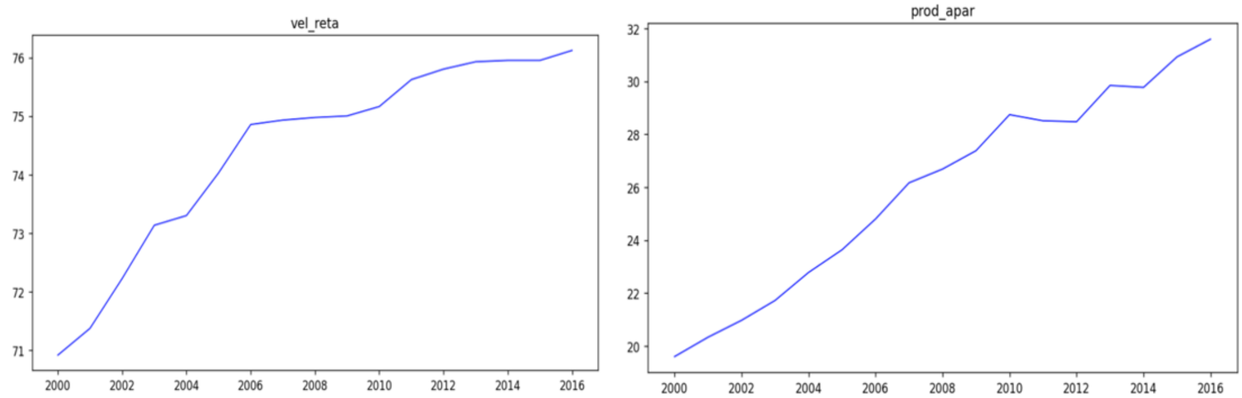


Figure 10. Straight equivalent speed (national average timeseries) on the left and apparent labour productivity (national average timeseries) on the right.

The results reveal that, at a 5% significance level, straight equivalent speed Granger-causes apparent labour productivity; thus, there appears to be evidence that a rise in straight equivalent speed leads to an increase in productivity at the aggregated national level.

The authors also tested the causation of the two remaining transportation factors under consideration (road accessibility and sinuosity index), but both failed to demonstrate causality at the national level. In various cases, the authors found the sinuosity index and straight equivalent speed to "Granger-cause" apparent labour productivity at the regional level. Only in the case of Alentejo Central did road accessibility "Granger produce" apparent labour productivity, as seen in **Table 6**.

Table 6. Granger causality analysis.

Region	Sinuosity	Straight equivalent speed	Road accessibility	Jobs	Total investment rate
Alto Minho	0.833	0.451	0.915	0.006*	0.001*
Alto Tâmega	0.000*	0.128	0.637	0.914	0.476
Alentejo Central	0.491	0.000*	0.012*	0.247	0.262
Cávado	0.952	0.926	0.904	0.000*	0.083
Ave	0.0418*	0.005*	0.863	0.0013*	0.611
Área Metropolitana do Porto	0.051	0.0046*	0.488	0.0069*	0.0014*
Tâmega e Sousa	0.055	0.0072*	0.799	0.0377*	0.105
Douro	0.129	0.075	0.564	0.390	0.930
Terras de Trás os Montes	0.002*	0.0215*	0.588	0.619	0.929
Oeste	0.287	0.104	0.231	0.543	0.744
Região de Aveiro	0.575	0.0194*	0.445	0.619	0.517
Região de Coimbra	0.128	0.0031*	0.705	0.474	0.457
Região de Leiria	0.400	0.659	0.478	0.000*	0.335
Viseu Dão Lafões	0.335	0.979	0.776	0.0102*	0.868
Beira Baixa	0.378	0.796	0.770	0.060	0.807
Médio Tejo	0.182	0.388	0.364	0.0324*	0.392
Beiras e Serra da Estrela	0.595	0.000*	0.423	0.925	0.995
Área Metropolitana de Lisboa	0.000*	0.0002*	0.094	0.106	0.000*
Alentejo Litoral	0.231	0.333	0.596	0.309	0.266
Baixo Alentejo	0.000*	0.0301*	0.297	0.227	0.125
Lezíria do Tejo	0.0001*	0.230	0.067	0.190	0.357
Alto Alentejo	0.0416*	0.839	0.959	0.417	0.0388*
Algarve	0.0128*	0.073	0.088	0.009*	0.0008*

* *p-value < 5%.*

Overall, raising straight equivalent speed, or the sinuosity index, would increase apparent productivity for the typical Portuguese region at the regional level.

Figure 11 depicts a map of the spatial distribution of granger-causality results. The places where each of the primary two transportation factors has been proved to granger-cause apparent labour productivity are highlighted in green.

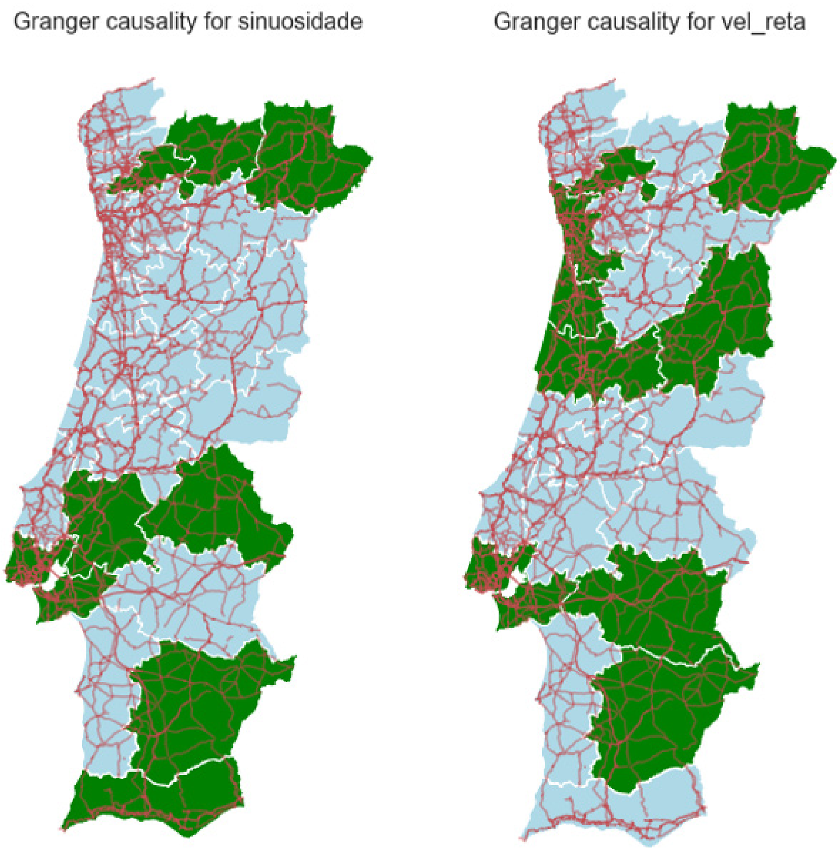


Figure 11. Granger causality and the road network.

Table 7 displays the results of the reverse granger-causality test, which was used to determine whether the causality connection could be reversed. Only in a few situations, there is evidence of granger-induced transport variables caused by apparent labour productivity. However, there is larger evidence on employment and private investment: both have been shown to be granger-caused by apparent labour productivity in multiple circumstances.

4.4. Spillover effects

Section 4.2 has shown that there is an apparent spatial relation between apparent labour in different regions. The literature provides evidence that spillover effects occur in productivity, especially in the context of accessibility increases (see Section 2.2) and, thus, they should be accounted for. This subsection aims to determine whether there is any relevant spillover effect.

A cross-sectional model was developed to examine nearby regions' spatial influence. The initial step was to compute the centroid for each of our 23 regions (**Figure 12**).

Table 7. Reverse granger-causality results for apparent labour productivity.

Region	Sinuosity	Straight equivalent speed	Road accessibility	Jobs	Total investment rate
Alto Minho	0.799	0.800	1.000	0.000*	0.000*
Alto Tâmega	0.511	0.681	0.875	0.175	0.829
Alentejo Central	0.798	0.418	0.989	0.002*	0.339
Cávado	0.257	0.123	0.793	0.000*	0.928
Ave	0.029*	0.036*	0.613	0.039*	0.487
Área Metropolitana do Porto	0.394	0.151	0.864	0.094	0.021*
Tâmega e Sousa	0.897	0.992	0.915	0.023*	0.014*
Douro	0.389	0.430	0.581	0.879	0.408
Terras de Trás os Montes	0.339	0.418	0.739	0.791	0.078
Oeste	0.350	0.890	0.845	0.779	0.688
Região de Aveiro	0.229	0.879	0.558	0.083	0.556
Região de Coimbra	0.633	0.181	0.191	0.020*	0.013*
Região de Leiria	0.859	0.617	0.749	0.005*	0.000*
Viseu Dão Lafões	0.981	0.468	0.200	0.532	0.857
Beira Baixa	0.426	0.701	0.267	0.139	0.808
Médio Tejo	0.220	0.584	0.655	0.000*	0.464
Beiras e Serra da Estrela	0.033*	0.113	0.517	0.687	0.027*
Área Metropolitana de Lisboa	0.600	0.899	0.667	0.174	0.171
Alentejo Litoral	0.011*	0.020*	0.802	0.330	0.044*
Baixo Alentejo	0.150	0.283	0.933	0.263	0.705
Lezíria do Tejo	0.061	0.816	0.815	0.000*	0.031*
Alto Alentejo	0.019*	0.223	0.326	0.000*	0.442
Algarve	0.010*	0.058	0.258	0.000*	0.137

* *p-value < 5%.*

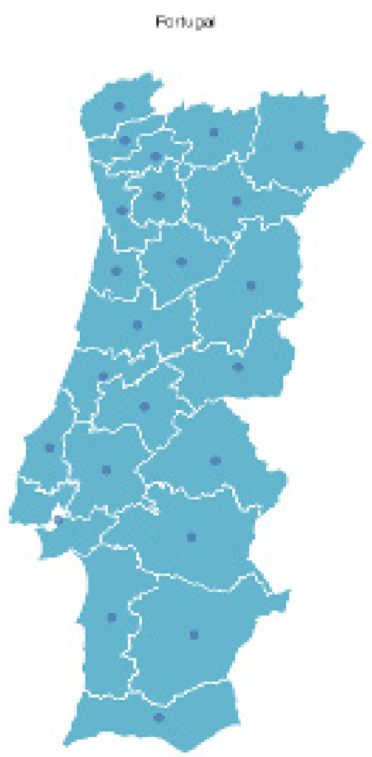


Figure 12. Centroids for each NUTSIII.

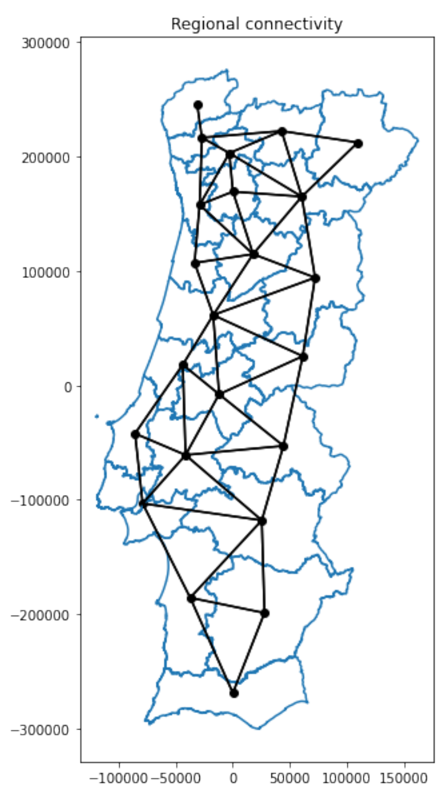


Figure 13. Regional connectivity.

Each centroid is linked to its nearest neighbour to construct a geographic network (**Figure 13**). Then, the influence of each neighbour is weighted and normalized in each row of the spatial proximity matrix based on the determined road distance between each node.

Using the model described in the methodology (Section 3), one regression may be obtained for each region, isolating the spillover effects on each region. The values acquired will translate the region's average spillover effect to its neighbours. To represent this time series, it was necessary to mathematically change it by using a log transformation and a first differential.

Regression coefficients should be interpreted as the positive or negative influence of a 1% rise in our independent variable on the increase in perceived labour productivity, our dependent variable. For example, in the case of spatial productivity in Médio Tejo, the model predicts that a 1% increase in productivity in neighbouring regions will result in a 0.99% increase in output in Médio Tejo.

The model produces the best results using straight equivalent speed as our transport variable. However, it was not possible to provide good results for the regions of Cávado, Viseu Do e Lafes, Beira Baixa, Alentejo Litoral, Baixo Alentejo, and Algarve (p-value of F-stat is higher than the significance level of 5%). There is no evidence that including independent variables improves the overall predictive power of the models discussed above.

Table 8 displays the results. The findings indicate that productivity has a beneficial spillover impact throughout the country. Increased production in these locations will result in increased productivity in neighbouring regions. This was expected given the favourable spatial correlation in apparent labour productivity.

Regarding the influence of spatial transport variables (straight equivalent speed), four significant coefficients exist in the Alentejo Central, Ave, Oeste, and LMA regions. The coefficient indications are as expected in the regions of Oeste and LMA but are opposite in the regions of Alentejo Central and Ave.

The models show that investing in transportation infrastructure in the neighbouring regions of Alentejo Central, Alentejo Litoral, Lezíria do Tejo and Região de Leiria has a positive effect on productivity of 3.10% (LMA) and 3.92% (Oeste).

Some results are more difficult to explain; for example, the coefficients found in Alentejo Central and Ave are negative, and the self-transport variable has a substantial value in the model of Oeste, which is contrary to expectations.

Perhaps the large disparity in perceived labour productivity between Alentejo Central and Oeste and its neighbours is one of the causes of their surprise coefficients. In the case of Ave, the fact that it is part of an LL cluster may be affecting its spillover effects. Nonetheless, more research is required to understand the phenomenon better.

5. Conclusions

Transportation systems, specifically the infrastructure stock and overall accessibility they offer (average accessibility, proximity to ports or airports, etc.), can play an essential role in the spatial analysis of economic and social trends. However, the previously described efficiency levels

Table 8. Results for regression and spatial spillover.

Region	*R*-squared	*F*-stat	MSE	AIC	Constant	Self-transport	Spatial-productivity	Spatial-tranport
Alto Minho	0.519	4.669**	0.005	–64.969	0.001	4.890	1.376***	–4.552
	(0.407)****				[–0.016, 0.018]	[–8.152, 17.932]	[0.521, 2.231]	[–14.971, 5.866]
Alto Tâmega	0.572	5.792**	0.006	–65.797	–0.002	0.163	1.201***	–0.784
	(0.473)				[–0.018, 0.015]	[–0.81, 1.135]	[0.566, 1.838]	[–1.956, 0.389]
Alentejo Central	0.540	5.081**	0.008	–58.435	–0.001	3.491	0.350**	–5.794
	(0.433)				[–0.022, 0.019]	[–3.788, 10.771]	[0.028, 0.672]	[–10.504, –1.084]
Cávado	0.310	1.949	0.001	–82.680	–0.001	0.309	0.436**	–0.284
	(0.151)				[–0.011, 0.009]	[–3.225, 3.843]	[0.014, 0.86]	[–2.801, 2.233]
Ave	0.602	6.557**	0.002	–85.492	–0.001	0.349	0.742***	–1.308**
	(0.510)				[–0.01, 0.009]	[–0.811, 1.509]	[0.333, 1.151]	[–2.417, –0.201]
Área Metropolitana do Porto	0.620	7.059**	0.003	–81.728	–0.001	3.997	0.724**	–3.985
	(0.531)				[–0.012, 0.009]	[–1.914, 9.909]	[0.189, 1.26]	[–8.646, 0.676]
Tâmega e Sousa	0.636	7.562**	0.003	–82.646	–0.001	0.732	1.004***	–0.283
	(0.551)				[–0.011, 0.009]	[–0.528, 1.992]	[0.54, 1.469]	[–2.043, 1.476]
Douro	0.850	24.542**	0.008	–83.853	0.003	–0.442	1.416***	1.591
	(0.815)				[–0.007, 0.013]	[–1.812, 0.927]	[0.959, 1.874]	[–0.336, 3.519]
Terras de Trás os Montes	0.679	9.158**	0.007	–71.478	0.000	0.595	0.798***	–0.655
	(0.604)				[–0.014, 0.014]	[–0.851, 2.041]	[0.401, 1.196]	[–2.852, 1.542]
Oeste	0.767	14.249**	0.007	–76.856	–0.005	–6.832**	1.189***	3.925***
	(0.713)				[–0.018, 0.009]	[–12.34, –1.324]	[0.772, 1.607]	[1.427, 6.424]
Região de Aveiro	0.542	5.130**	0.002	–82.289	0.000	1.500	0.634***	–0.709
	(0.436)				[–0.01, 0.011]	[–4.795, 7.794]	[0.28, 0.99]	[–4.74, 3.321]
Região de Coimbra	0.758	13.598**	0.005	–82.663	–0.001	–0.244	1.243***	0.122
	(0.703)				[–0.011, 0.009]	[–1.701, 1.213]	[0.808, 1.678]	[–1.092, 1.336]
Região de Leiria	0.753	13.176**	0.003	–89.143	–0.002	1.362	0.658***	–2.738
	(0.695)				[–0.011, 0.006]	[–0.988, 3.712]	[0.422, 0.896]	[–7.642, 2.166]
Viseu Dão Lafões	0.430	3.264*	0.002	–70.620	–0.001	–1.355	0.634**	0.178
	(0.298)				[–0.016, 0.013]	[–4.106, 1.396]	[0.011, 1.258]	[–2.63, 2.986]
Beira Baixa	0.271	1.612	0.002	–64.199	0.000	–0.049	0.487*	–0.713
	(0.103)				[–0.017, 0.017]	[–0.749, 0.651]	[–0.053, 1.027]	[–2.929, 1.503]
Médio Tejo	0.683	9.334**	0.005	–76.218	0.001	0.169	1.098***	0.950
	(0.609)				[–0.012, 0.013]	[–1.314, 1.651]	[0.636, 1.56]	[–0.334, 2.233]
Beiras e Serra da Estrela	0.614	6.894**	0.005	–71.520	–0.002	–0.020	1.005***	–0.828
	(0.524)				[–0.016, 0.012]	[–0.588, 0.549]	[0.499, 1.511]	[–2.285, 0.63]
Área Metropolitana de Lisboa	0.750	13.005**	0.002	–95.916	0.000	–1.362	0.620***	3.104**
	(0.692)				[–0.006, 0.007]	[–3.775, 1.051]	[0.406, 0.836]	[0.239, 5.97]
Alentejo Litoral	0.266	1.569	0.024	–19.212	–0.003	10.643	1.277	–7.156
	(0.096)				[–0.069, 0.063]	[–5.14, 26.426]	[–0.969, 3.524]	[–20.923, 6.61]
Baixo Alentejo	0.245	1.409	0.011	–30.257	–0.012	–13.642	0.0916	4.320
	(0.071)				[–0.06, 0.037]	[–31.054, 3.77]	[–0.678, 0.861]	[–6.56, 15.2]
Lezíria do Tejo	0.702	10.218**	0.007	–71.278	0.000	–5.241*	1.078***	–0.051
	(0.633)				[–0.014, 0.014]	[–11.497, 1.014]	[0.565, 1.592]	[–2.451, 2.349]
Alto Alentejo	0.591	6.254**	0.005	–70.992	0.001	0.961	0.750***	0.460
	(0.496)				[–0.014, 0.015]	[–2.134, 4.056]	[0.372, 1.129]	[–3.727, 4.647]
Algarve	0.238	1.353	0.001	–70.361	–0.002	–0.036	0.083	1.188
	(0.062)				[–0.016, 0.013]	[–1.303, 1.232]	[–0.047, 0.214]	[–2.42, 4.796]

** p-value < 10%; ** p-value < 5%; *** p-value < 1%; **** adjusted R-squared.*

constitute a “firm-centered” analysis and do not clearly evaluate the transportation system’s true spatial impact.

As a result, the spatial impact on productivity was examined in this study. Rather than doing a detailed research on productivity drivers, the authors aimed to explore the potential (as)symmetries that have emerged due to transportation system growth.

This study has the advantage of focusing on accessibility from the perspective of the actual effects that infrastructure improvement has on the territory, rather than investment (as many previous studies have done). The use of investment indicators (total investment, investment growth, or even infrastructure capital stock) assumes that increased investment would result in proportionally better accessibility and mobility. This is not always the case. For example, the average cost per kilometre of transportation infrastructure (road or railway) can vary greatly depending on the region’s physical qualities. As a result, a certain location may benefit from a high level of investment without a commensurate accessibility improvement. To put it another way, the elasticity of accessibility to investment may differ. Quality is defined as the match between the infrastructure and the demand it supports.

Our findings indicate that accessibility is important, but not all kinds of accessibility. Road travel times have decreased overall in the road system due to significant investment in road stock since the 1990s. The construction of the road system, particularly highways, was a clear political goal. In the 1990’s until late 2000’s, both local and central governments developed a strategy towards favouring road investment. With the economic development post-EU adhesion, there was a social bias towards car-ownership and car utilization, and the (over) development of the highway system allowed for political gains. While road accessibility improved, rail accessibility behaved quite differently. Because of the overall reduction and disinvestment in the network, rail travel times have increased in various regions. In fact, rail-related variables add little to our knowledge of productivity.

The results demonstrate that transportation variables have a high connection with productivity, albeit road-related variables are dominant, as are distances to ports and seaports, the latter of which are likely related to proximity to the shore. Railway variables have no apparent impact. According to the findings, sinuosity, straight equivalent speed, and road accessibility have a stronger link with apparent labour productivity. This verifies our initial idea that it is vital to pick the transport variables utilized in productivity analysis carefully and that physical accessibility can be more important than simple infrastructure investment or infrastructure stock. Furthermore, the investigation revealed that there are meaningful spill-over impacts to consider when analyzing productivity, particularly in the LMA.

Future research should include a more extensive investigation at the municipality level, rather than NUTs III, to capture possibly relevant changes between municipalities.

Author contributions

Conceptualization, JFJ, COC, JMS and ÁC; methodology, JFJ and COC; software, JFJ; validation, COC, VFS and JMS; formal analysis, JFJ; investigation, JFJ and COC; JMS, ÁC and VFS; resources, COC; data curation, JFJ; writing—original draft preparation, JFJ; writing—review and editing, COC, JMS, VFS and ÁC; visualization, JFJ; supervision, COC; project administration,

COC; funding acquisition, COC. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare no conflict of interest.

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