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Elena Calegari

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Abstract. Applying a two-stage methodology that uses the distance decay gradient as measure of commuting behaviour, the article examines the effect of the spatial characteristics of the economic activities on commuting. The model, applied to Italian Travel To Work Areas, includes both some of the main spatial characteristics gathered from the literature and some new ones, aimed at testing if the socio-economic features of the area influence the effect the spatial characteristics on commuting. Estimates show that in more polycentric areas the decrease in the amount of commuters due to increases in commuting distance is, on average, higher than in more monocentric ones but that effect strongly depends on the industrial composition of the economy. Moreover, high level of urbanization economies leads to a less steep gradient, especially associated with a high share of high-skilled workers, describing a smoother decrease of commuting flows as the distance between job location and residence location increases. In addition, results show how most of these effects are not highlighted using the average commuting distance as measure of commuting behaviour.

Keywords. Commuting, Spatial Structure, Distance-decay gradient, Two-stages model.
J.E.L. **classification.** R12, C21.

1. Introduction

Commuting is acknowledged worldwide as a crucial mechanism to enable individuals to participate in the labour market, but also as a source of negative externalities, such as pollution and traffic congestion (van de Coevering and Schwanen, 2006). For these reasons, many researches focus either on its determinants or on its consequences. In particular, being commuting essentially a spatial equilibrating mechanism between labour demand and supply within a certain area (Persyn and Torfs, 2015), most of the studies on its determinants analyse the relationship between the spatial characteristics of the area, such as employment density or job-housing imbalance, and commuting distance (Boussauw et al., 2012; Levine, 1998).

The average commuting distance within a certain area can be seen as the outcome of two different relationships: a pure spatial relationship, that depends on physical locations, and a behavioural relationship, based on the individual willingness to commute. Indeed, on the one hand, the average commuting distance is due to the conditional spatial distribution of jobs and residences, and, on the other hand, it is the result of the reduction of the commuting flows as the distance between job location and residence location increases. The present paper analyses this second relationship, by estimating how spatial characteristics of the labour market influence the decrease in commuting flows due to increments in commuting distance. The literature on how spatial features affect commuting behaviour mostly focuses on characteristics such as the polycentricity, job-housing imbalance and urban density (Aguilera, 2005; Giuliano and Small, 1993), whereas only few studies examine the relationship between commuting and agglomeration economies (Melo et al., 2012). However, results depend on how commuting behaviour is measured. Indeed, most of the previous studies adopt the average commuting distance or time (Cervero and Wu, 1998; Engelfriet and Koomen, 2018), whereas only few exploit different measures (Melo et al., 2012).

Among the spatial attributes widely recognized for their effect on commuting behaviour measured in terms of average commuting distance, there are polycentricity, job-housing imbalance, urban density, and urban shape. According to the predictions of the monocentric model, given a decrease in transport costs due to the reduction of the price of the engine, both employment and population should move away from the central business district and spread across several sub-centres into a polycentric form, leading to a reduction of the average commuting distance (Glaeser and Kahn, 2004; Glaeser and Kohlhase, 2004). Nevertheless, empirical evidence on the effect of polycentricity on commuting is mixed (Boarnet, 1994; Cervero, 1996); in some studies the estimated average commuting distance is lower in polycentric areas than in monocentric ones, whereas others find the opposite relationship (Aguilera, 2005; Cervero and Wu, 1998; Gordon et al., 1989). The authors explain their result underlying that, being the relocation process of jobs slower than the relocation of households, in polycentric systems where the process is incomplete, more jobs than workers are located in certain sub-centres, leading workers that do not live in those sub-centres to commute longer distance. Also, the job-housing imbalance, that is the location of the employment with respect to residential areas, influences commuting distance. If jobs are far away from houses, then the commuting distance tends be higher, especially for workers with high relocation costs (Cirilli and Veneri, 2014; Giuliano and Small, 1993). With respect to the urban density, studies that examine the effect of compactness of cities on commuting distance show that both high residential and employment densities are associated with shorter commute (Boussauw et al., 2012; Giuliano and Narayan, 2003). Finally, also the urban shape has shown to have a small but significant effect on the average commuting distances, that tend to be longer in larger and narrower urban areas than in smaller and circular ones (Bento et al., 2005).

Another set of spatial characteristics that may affect commuting behaviour concern the spatial concentration of the economic activities. In particular, agglomeration economies have been tested both as localization economies and urbanization economies. The former, that refers to the gain for firms of the same industry located in clusters, is found to be associated with longer commuting, and the latter, described as the overall benefit that economic activities receive when they are concentrated across space, displays the same effect (Fujita and Thisse, 1996; Melo et al., 2012).

However, even if each of the aforementioned spatial characteristics have been shown to affect commuting behaviour individually, previous studies do not account for the fact that the effect of some of them could be mediated by other, not-spatial, features of the area. Starting from the consideration that the spatial structure may not be sufficient to explain substantial changes in aggregate travel patterns, and that also local socio-economic features contribute in shaping commuting distances (Lin et al., 2015; van de Coevering and Schwanen, 2006), in the present paper two main hypotheses are tested: a) The effect of polycentricity depends on the structure of the local economy; b) The effect of urbanization economies depends on the share of workers with a tertiary education degree.

The first hypothesis finds its rationale on the fact that, in areas with high level of polycentricity, the reduction of commuting distance expected by the monocentric model might be impeded by the industrial composition of the economy. Indeed, for areas with high shares of industries with propensity to cluster, commuters could be forced to travel longer distances (Zhao et al., 2011). The second hypothesis grounds on the pieces of evidence that higher skilled workers tend to commute more in order to find a proper job (Rouwendal and Rietveld, 1994; Schwanen et al., 2001), and that high skilled job-places tend to be clustered, thus suggesting that the effect of urbanization economies on commuting is likely to depend on the level of education in the area. Indeed, it is possible that the increase of commuting distance due to urbanization economies is strengthened in areas characterized by higher level of education. In labour markets with high demand for high skilled workers, the urban structure becomes the core of the labour market, attracting most of the workers and forcing the ones that live outside the urban area to be willing to commute longer distances to exploit their skills.

From a methodological perspective, although previous studies on the effect of spatial characteristics on the average commuting distance give useful insights, they ignore that the average distance within a certain area results from two distinct mechanisms: on the one hand, it depends on the spatial distribution of jobs and residences in the area but, on the other hand, it is also depends on the expected reduction of commuting flows due to increments in commuting distance. With respect to the latter mechanisms, evidence shows that commuting flows between locations decrease if the distance between those locations increases, but also that this reduction varies among pairs of locations. In policy terms, it has the consequence that an equal increase in commuting distance between job and residence leads commuters to refuse jobs in some labour markets whereas it does not have the same effect in others. Therefore, to properly estimate the effect of spatial characteristics on commuting behaviour it is necessary to account for both mechanisms. In this direction, as pointed out by Melo et al. (2012), the distance decay gradient of the commuting flow is a more suitable measure of commuting behaviour than the commuting distance, because it gives information about the degree to which distance is perceived as an obstacle in commuting, conditional to the spatial structure of the area (Fotheringham, 1981).

The paper aims to answer two main questions: *Which are the spatial characteristics that mostly influence commuting behaviour? Do the results differ using the distance decay gradient of a spatial interaction model to measure commuting behaviour instead of the average commuting distance?* Using the two-stage model introduced by Melo et al. (2012), in the present paper the influence of the main spatial characteristics on commuting behaviour is tested by including new spatial features, based on the predictions of the agglomeration theory and the monocentric model. Furthermore, the analysis has the scope to compare results based on the distance decay gradient of commuting flows and the average commuting distance as measures of commuting behaviour in spatial context. The model is applied to the Italian Travel To Work Areas (TTWAs), used as approximation for the labour markets in Italy.

The structure of the paper is the following: in Section 2 the methodology used for each of stage of the model is reported, as well as the main spatial variables included in the analysis; in Section 3 the empirical results are described and in Section 4 the main conclusions are highlighted.

2. Methods

To examine the effect of spatial characteristics on commuting behaviour, a two-stage estimation procedure is employed, as proposed by Melo et al. (2012). The rationale behind the model is that the distance decay gradient of a spatial interaction model for commuting captures the relationship between observed commuting flows and distance better than the measures used in previous literature, as the average commuting distance.

The empirical application is addressed to Italy and focuses on the commuting behaviour within the TTWAs. The TTWAs in Italy are built in accordance with the international definition, as groups of municipalities where at least the 75% of inhabitants that live there, work there.

In the first stage the distance decay gradient of a spatial interaction commuting flow model is estimated for most of the Italian TTWAs, seen as geographical units that contain most of the local commuting flows. In the second stage the estimated parameter is regressed on selected spatial characteristics of the TTWAs.

2.1. The first stage

In the analysis of aggregate commuting flows, the spatial interaction model is widely used (Persyn and Torfs, 2015). The main idea of this approach is that the size of commuting flow between two municipalities depends negatively on the distance between them and positively on their sizes.

A basic specification of the model has been proposed in a seminal paper by Fotheringham and O'Kelly (1989):

$$F_{ij} = cV_i^{\alpha} V_j^{\beta} f(d_{ij}), \tag{1}$$

where F_{ij} denotes the number of commuters between the municipality of origin i and the municipality of destination j, c is a constant, V_i and V_j are measures of the size of origin and destination, usually measured as the total population at the origin and the employment in the destination. d_{ij} measures the distance between i and j, $f(d_{ij})$ defines the functional form of the distance and α and β are parameters to be estimated[1].

In the proposed model a power function is used as functional form of the distance, leading to the following specification:

$$F_{ij} = cV_i^{\alpha} V_j^{\beta} d_{ij}^{\gamma}, \tag{2}$$

This functional form has been preferred with respect to the exponential one to account for the heterogeneity in commuters and for the presence of spatial-economic disparities among areas (Wilson, 1967). Indeed, it has been shown that, deriving from a logarithmic form of the cost function of travelers, the power-form is suggested in presence of heterogeneous groups of trip makers, whereas the exponential-form is associated with the perception of costs of more homogeneous commuters (Fotheringham and O'Kelly, 1989; Reggiani et al., 2011; Williger s, 2006). Moreover, the chosen form returns scale-independent parameter estimates, making them more useful for the transferability of results (Reggiani et al., 2011).

The parameter γ estimated through the spatial interaction model stated in Equation 2 is called distance decay parameter and measures the relationship between observed commuting flows and commuting

[1] To the general formulation, distance can be measured as physical distance, monetary costs or time spent.

distance, holding fixed all the other determinants. This relationship is expected to be negative, estimating the decrease in commuting flow due to a unitary increment in commuting distances; for this reason γ is also known as distance decay gradient. Moreover, the distance decay gradient has been recognized as an accurate measure of the perception of distance as deterrent in commuting as well as a function of the spatial structure of the origin and destination locations of the flows (Curry, 1972; Fotheringham and Webber, 1980). Fotheringham (1981) not only reports pieces of evidence of the spatial nature of the distance decay gradient, but also theoretically proves that the parameter depends on the spatial structure of the locations involved in the interaction. A piece of evidence that is particularly relevant for the current research is that, if the estimated distance decay gradient was just a function of the interaction behaviour, a positive relationship between the parameter and the average commuting distance would always hold; in some cases, however, the correlation between the distance decay gradient and the average distance is negative (Stillwell, 1978). This result might be explained through the fact that, if locations with low degree of accessibility are involved in the commuting interaction, the estimated distance decay gradients are negative as expected but higher in magnitude, leading the correlation between the parameter and the average commuting distance to be negative as well. This characteristic justifies the research question "Do the estimates of the effects that spatial characteristics have on commuting differ using the distance decay gradient of a spatial interaction model to measure commuting behaviour instead of the average commuting distance?". Moreover, it makes to suppose that, since the distance decay parameter is a function of the spatial structure, as described in equation (33) of Fotheringham (1981), it is more suited to evaluate the effect of the spatial characteristics on commuting behaviour than the average commuting distance. Indeed, it allows us to decompose the overall effect of the spatial structure in separate effects of single spatial characteristics.

To estimate the distance decay gradient for the TTWAs in Italy, the proposed model includes only commuting flows between municipalities within TTWAs[2]. The Euclidean distance between the centroids of the municipalities has been considered as measure of distance and, to account for flows within the same municipality, the distance is assumed to be proportional to the square root of the area of the municipality (Persyn and Torfs, 2015)[3]. It is worth noting that the Euclidean distance is a proxy of the actual commuting distance containing both a measurement error, related to the calculation algorithm, and a spatial error, since it does not consider the actual transport network. However, previous literature adopting Euclidean distance shows robust results (Melo et al., 2012; Persyn and Torfs, 2015)[4].

To the general formulation, as it is common in the literature, the logarithm on both sides of Eq. 2 has been taken (Fotheringham and O'Kelly, 1989). Moreover, being aware of the possible concerns about the OLS estimation for count data as commuting flows, the model has been estimated both with the OLS estimator and a Poisson Pseudo Maximum Likelihood estimator, obtaining more robust results with the latter (Cameron and Trivedi, 1998; Santos Silva and Tenreyro, 2006)[5].

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[2] Therefore, commuters who work in a different TTWA with respect to the one where they live, as well as the cross-border commuters, have been excluded from the analysis.

[3] The commuting distance for workers that live and work in the same municipality i is calculated according to the formula: $d_{ii} = (2/3) \cdot \sqrt{area_i \pi}$.

[4] For completeness, as robustness check in the Appendix, the estimates of the distance decay gradient calculated using the travel time instead of the Euclidean distance have been reported. The results, shown in Table A1 in the Appendix, are comparable with the ones estimated by means of the distance, even if the latter seem to be more robust. This might be due to the nature of the declared travel time variable included in the data. Indeed, the travel time is measured as a categorical variable, that in the analysis has been approximated using the average value of each category. Also, for origin-destination pairs with no declared travel time, it has been predicted as a linear function of the existing observations.

[5] Two main issues arise applying the OLS estimator in the context of spatial interaction modelling for commuting flows. First of all, the error term is likely not to be homoskedastic and, secondly, the OLS has a problem in dealing with zero flows since it is not possible to compute the log of zero, loosing relevant information.

To estimate for each TTWAs the theoretical model stated in Eq. 2 through Poisson Pseudo Maximum Likelihood regression, the model specification is the following:

$$\begin{aligned} logF_{ij} &= logc + \alpha\ logPopOrigin_i + \\ &+ \beta\ logEmpDest_j + \gamma\ Distance_{ij} + \phi_i + \omega_j + \varepsilon_{ij}, \end{aligned} \tag{3}$$

where $logF_{ij}$ denotes the logarithm of the number of commuters between the municipality of origin i and the municipality of destination j (within the TTWA) and c is a constant. The size of the municipality of origin is measured with the total population ($PopOrigin_i$) in logarithm, whereas the size of the municipality of destination is given by the total employment ($EmpDest_j$) in logarithm. γ is the distance decay parameter, that is the parameter of interest, and is interpretable as an elasticity. Finally, α and β are other parameters to be estimated and ε_{ij} is the error therm. To control for origins and destinations' possible specificities, the model includes origin and destination fixed effects ϕ_i and ω_j.

2.2. The second stage

The second stage relates the main spatial characteristics of the TTWA, that describe the spatial distribution of economic activities across the TTWA as well as the relative position of jobs with respect to households, to the distance decay gradient estimated for each TTWA at the first stage of the model (Melo et al., 2012). The absolute value of the distance decay gradient estimated at the first stage is thus the dependent variable in the second stage, which uses the main relevant spatial characteristics of the labour market as explanatory variables[6]. The estimated model is:

[6] Keeping in mind that the distance decay gradient assumes negative values, the absolute value has been taken to facilitate the interpretation of the results.

$$|\gamma_c| = a_c + \sum_k^K b_{ck} \boldsymbol{X}_{ck} + \mu_c, \tag{4}$$

where $c=1,...,C$ represents each TTWA, $\boldsymbol{X}_{ck}$ is the set of spatial explanatory variables for the c-th TTWA, a_c is the constant term of the regression and μ_c is the error term.

To account for the fact that the dependent variable in the regression is an estimate, and therefore has different precision for each TTWA, the model is estimated applying a Weighted Least Square regression that adopts as weights the inverse of the standard errors of each estimate (Cameron and Trivedi, 2005).

In the final model seven explanatory variables are included, of which four are spatial characteristics and the other three are interaction terms used to test if the effect of certain spatial characteristics depends on socio-economic features of the TTWA. In addition, a set of controls is included.

The first spatial characteristic included in the model is the job-housing imbalance, measured as the Gini Index between the total work force and the employment among the municipalities in the TTWA. This index is a measure of concentration and allows to quantify the degree to which the jobs are evenly distributed relatively to where workers live; it takes values close to 0 for an even distribution of job places and working population in the TTWA, whereas it assumes values close to 1 if all the job places are concentrated in few municipalities with respect to the ones where workers live. The index has been computed plotting the cumulative distribution of the jobs of the municipalities within the TTWA (y-axis) against the cumulative distribution of the active population for the same municipalities (y-axis), obtaining the Lorenz curve. Then, the Gini coefficient is given by the ratio of the area between the Lorenz curve and the 45° line (curve for perfectly even distribution of jobs and residences) and the total area under the 45° line (Bento et al., 2005).

The second characteristic is the employment density, measured as the number of employed persons per km^2, and seen as a description of the compactness of the TTWA.

Also, the level of polycentricity of the TTWA has been included. It is measured as the estimate of the β parameter of the following equation:

$$log(Emp_i) = \alpha - \beta\, d_i + u_i, \qquad (5)$$

where Emp_i is the employment density at the municipality i, d_i the distance from the municipality i and the central business district (CBD) municipality of the TTWA and u_i the error term. From this estimation, the parameter β is the gradient that shows the reduction of the density caused by a unitary increment in the distance (McMillen, 2007). Therefore, the value of the gradient can be either negative or positive, showing different degrees of polycentricity of the TTWA. Strongly negative values of the β show that the employment density decreases as long as municipalities are far from the CBD, suggesting for a monocentric TTWA, whereas a reduction of the magnitude of the negative value shows the reduction of the degree of monocentricity in favour of a more polycentric configuration, that becomes prevalent when β is positive. This measure, for construction, arises two main concerns. The first one is that, being an estimate, it contains an estimation error that might rise the standard error of the coefficient of interest; the second one is that, being a measure that covers the entire range of the monocentricity-polycentricity relationship, it is likely to have a not-monotonic effect on the dependent variable[7].

To know if the level of agglomeration economies influences commuting behaviour two other explanatory variables have been included. The first one is the Hirshmann-Herfindhal Index for the TTWA, whose aim is to account for the localization economies. It is computed as follows:

[7] To address the last issue, the specification of the model containing polycentricity in a quadratic form has been tested. Results shows that, even if the quadratic terms is significant for the basic model, it is not significant any more once more explanatory variables are included in the specification.

$$HHI_c = \sum_{0>m>M} \left(\frac{E_{cm}}{E_c}\right)^2, \tag{6}$$

where c represents the *c-th* TTWA, E_{cm} is the employment in the industry m in the TTWA c, E_c is the total employment in the TTWA. The index assumes values between (1/M), in case of perfect diversity, and 1, in case of perfect specialization[8]. The second variable related to agglomeration economies is the Urbanization Index, that is meant to measure urbanization economies. It is measured as the share of the total employment of the TTWA located in urban municipalities, and ranges from 0, if the employment is totally distributed in sparsely populated municipalities, to 1, if the employment is totally located in urban areas. One concern about this measure is that its values strongly depend on the criteria applied to define urban municipalities, that can be fairly different among statistical offices, making results not perfectly comparable[9].

To test for the two hypotheses described in Section 1, concerning the influence that socio-economic features may have on the relationship between spatial characteristics and commuting behaviour, a set of interaction variables have been included in the model. To facilitate the interpretation of the interaction terms, they have been calculated as follows: given two characteristics generically called X_1 and X_2 included in Eq. 4, and being interested in estimate if the effect of X_1 on $|\gamma_c|$ depends on the levels of X_2, the estimated model is $|\gamma_c| = \beta_1 X_1 (X_1 - \overline{X_1})(X_2 - \overline{X_2}) + \ldots + \beta_k X_k + \ldots + \mu_c$, where $\overline{X_1}$ and $\overline{X_2}$ are the average values of the variables in the sample. According to this specification β_1 is the marginal effect of X_1 on the dependent variable at average level of X_2, whereas β_2 represents the change in the effect of X_1 on Y if X_2 assumes values higher than the mean. With this

[8] In the estimated model (Eq. 4) the index has been included in logarithmic form, to facilitate the interpretation of the coefficient.

[9] Here, to define urban municipalities, the Eurostat urbanization index is adopted. It assumes value 1 for urban municipalities, 2 for intermediate ones and 3 for thinly populated municipalities.

specification the standard errors of the interaction terms and the main variables can be interpreted directly.

The first hypothesis is whether the effect of polycentricity depends on the industrial composition of the TTWA. To test it, the economy of each TTWA have been divided in three main industries and for each industry the share of employment in that industry over the total employment in the TTWA has been computed[10]. Then, the interaction terms with the polycentricity degree have been created for each of these shares, but just two of them have been included in the final specification of the model to avoid multicollinearity[11]. The second hypothesis to be tested is whether the effect of urbanization economies on commuting depends on the level of education in the TTWA. To test it, the urbanization index has been interacted with the share of tertiary educated individuals over the total population of the TTWA.

To complete the estimated model a set of control variables have been included. To control for the transportation infrastructure supply, the road supply per km^2 have been included. If it is true that the transportation supply also includes other kinds of infrastructure, it is also true that Italian commuting is mainly performed by car and that only in specific TTWAs commuters choose the train or the metro. The level of congestion could also influence commuting behaviour. In previous literature, to measure road congestion to avoid possible endogeneity, the number of car accidents has been adopted (Cirilli and Veneri, 2014). However, also the km of road per inhabitant can be adopted to account for congestion. Another relevant control variable is the share of high-skilled workers in the TTWA. Indeed, previous literature shows that, on average, highly educated workers tend to have longer commuting trips. The last variable is meant to control for the friction due relocation cost in the TTWA and is the percentage of households who live in a house of property on the total number of households in the TTWA. Finally, since most of the public

[10] The first sector includes manufacturing and agriculture, the second includes finance, services and commercial activities, whereas the last sector includes the public sector.

[11] The industry that has been excluded is the service sector, chosen as reference category.

transportation supply and other characteristics as the level of maintenance of transport infrastructure are strongly related to the regional administration, dummy variables for each Italian region have been included[12].

The final list of variables considered for the second stage of the model is shown in the in Table 1.

[12] Previous studies also include the surface in km^2 and shape of the area in explaining the average commuting distance in the urban environment. In this application it is not the case because, since the TTWA are built according to commuting flows, those variables would have been strongly endogenous.

Description	Measure	Type of variable
Employment density	Number of workers per km^2	Main
Job-housing imbalance	Ratio of the area between the 45° line and the Lorenz curve drawn for cumulative distributions of jobs and active population (for municipalities within the TTWA) and the total area under the 45° line	Main
Polycentricity	Gradient of a regression for the employment density of each municipality on its distance with respect to the CBD of the TTWA (see Eq. 5)	Main
Urbanization Economies	Share of the employment in urban municipalities over the total employment	Main
Localization Economies	Logarithm of the Hirshmann-Herfindhal Index (see Eq. 6)	Main
Polycentricity × employment in agriculture and manufacturing	Polycentricity × Shares of employees in agriculture and manufacturing over the total employment in the TTWA	Interaction
Polycentricity × employment in public sector	Polycentricity × Shares of employees in the public sector over the total employment in the TTWA	Interaction
Urbanization Eco.× Tertiary education	Urbanization Economies × Share of individuals with tertiary education over the total population of the TTWA	Interaction
Road supply	Km of road per km^2	Control
Car accidents	Number of car accident per km^2	Control
Congestion	Km of road per inhabitant	Control
Percentage of house ownership	Percentage of households that live in their own property house over the total number of household in the TTWA	Control
Tertiary education	Share of individuals with tertiary education degree over the total population of the TTWA	Control

Data source: Italian National Statistical Office, 2011.

Table 1: Variables considered for the second stage of the model.

3. Empirical results

3.1. Data and summary statistics

The main data source for the empirical analysis is the Italian Population Census 2011, the last nationwide data collection where individuals have been asked to provide information about both their residential and job locations at municipality level, and the daily travel time spent in commuting. Origin-destination matrices of commuting flows are the core data for the analysis; therefore, all the other variables are collected for 2011. However, as highlighted by a recent paper by Gatto et al. (2020), the spatial pattern of commuting in Italy appears to be fairly preserved from 2011 onwards, despite the long time.

In 2011, about 19 million workers travel every day to their jobs, mostly by car[13]. In that year the TTWAs in Italy are 611 but, due to the strong heterogeneity among them, both in geographical and in economic terms, some TTWAs have been excluded from the analysis, leading to a final sample of 475 TTWAs (the 78% of the total)[14]. The highest number of TTWAs is located in the South of the country[15], whereas in the North are located both the biggest TTWAs in terms of population and, on average, the ones with the highest employment rate.

Summary statistics of these TTWAs are reported in Table 2. The area and the number of municipalities per TTWA describe the geographical size, the total population and the population density are

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[13] The 75% of the workers in the country use cars in their daily commuting, whereas 15% go walking. Just the 5.5% use public transportation, and the remaining 4.5% use either the bike or other means of transportation.

[14] Some examples of heterogeneity among Italian TTWAs: the number of municipalities per TTWA varies from 174 (for the Milan-TTWA) to 16, whereas the smallest TTWA in terms of geographical surface is more than 100 times smaller than the biggest one (that is the Rome-TTWA). The TTWAs that have been excluded from the analysis are the ones that exceed 3 standard deviations from each of the main dependent variables of the model.

[15] The number of TTWAs located in the South (including islands) represents the 46.0% of the total.

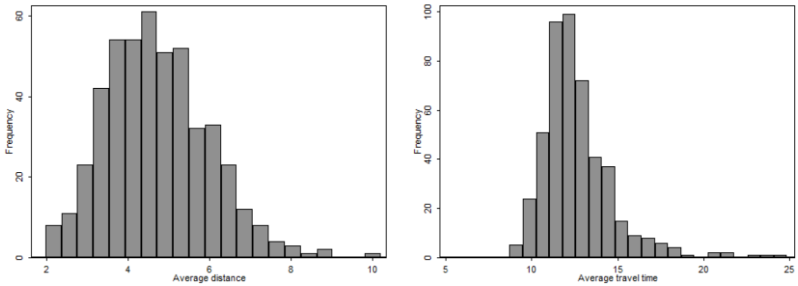
meant to show the social dimension, whereas the amount of workforce and the employment depict the economic size of the local labour markets. Considering that all the TTWA are built according to the same methodology, the strong differences among them suggest a remarkable diversification in the economic spatial environment across Italian TTWAs.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Area (km^2)	506	306	63	1,627
N. of municipalities	14	11	3	59
Population	88,114	155,183	3,138	2,510,848
Population density	196	278	10	3,107
Total workforce	38,053	62,224	1,568	916,396
Employment	33,456	50,980	1,463	664,542
Employment density	73	89	4	822
Job-housing imbalance	0.316	0.11	0.054	0.591
Polycentricity	-0.076	0.065	-0.285	0.076
Urbanization Economies	0.483	0.341	0	1
Localization Economies	0.236	0.023	0.194	0.322
N		475		

Table 2: Main characteristics of the Italian TTWAs in the sample.

The average commuting distance in Italy is around 5 km per trip and about the 90% of workers live within 7 Kms far from their jobs. In terms of commuting time, on average, commuters spend 13 minutes per trip and the 90% of them spend less than 16 minutes to reach their workplace. Both the average commuting distance and travel time are low compared to other European countries[16]; however, as shown in Figures 1.a and 1.b there is strong heterogeneity among areas. Finally, the average percentage of workers who work and live in the same municipality is around 35% per TTWA.

[16] For instance, the average travel time in the Netherlands is almost double than in Italy and more than double in the UK. (Source: OECD, 2005)



(a) Average travel distance per TTWA

(b) Average travel time per TTWA

Figure 1: Frequency of the average values of commuting distance and time per TTWA.

What emerges from the reported stylized facts is that Italian workers appear to be scarcely willingness to commute long distances or time to reach their job places. Thus, it is reasonable to suppose that, on average, Italian workers are very sensitive to increments in commuting distance and travel time in choosing their job location. This supposition is tested in the next Section.

3.2. First stage results: the distance decay gradient in the TTWAs

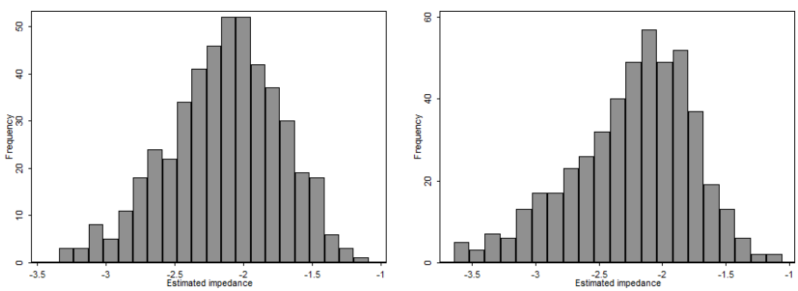
Table 3 reports the average value of the estimated distance decay gradient for the whole sample of TTWAs. The estimates are obtained adopting both OLS and Poisson regression following Eq. 3, using travel distance. The results obtained for travel time as a measure of commuting costs are reported in the Appendix.

	Mean	**Std.Dev.**	**Min.**	**Max.**
OLS	-2.144	0.410	-3.341	-1.088
Poisson	-2.236	0.476	-3.646	-1.055

Table 3: Average value of the distance decay gradient estimated with OLS and Poisson Pseudo-Maximum Likelihood estimators.

Both results are robust to robustness checks. Indeed, analogous values have been found dropping observations associated either to very short or long distances; moreover, the estimated distance decay gradients are significant for all the analysed TTWAs[17].

Since OLS estimation does not take into account the zero flows, it slightly underestimates the value of the distance decay gradient. Furthermore, on average, the Poisson regression registers lower AIC and an higher Log-Likelihood. Given the Poisson estimates, that can be interpreted as an elasticity, on average, 1% increment in commuting distance causes a decrease in commuting flows of about 2.2%, The histograms in Figure 2 a and b show the variation of the estimated distance decay gradient across TTWAs. As suggested by the stylized facts reported in Section 3.1 with reference to the average commuting distance, also the estimated distance decay gradient suggests that Italian workers are strongly sensitive to increments in commuting distance.



(a) Estimates of the distance decay gradient using OLS

(b) Estimates of the distance decay gradient using Poisson

Figure 2: Frequency distribution of the estimated distance decay gradient per TTWA.

[17] As first robustness check the observations associated to commuting distance lower than 3 kms have been excluded from the sample; as a second check have been excluded from the sample the observations with commuting distance higher than 35 kms.

3.3. Second stage results: Commuting behaviour and spatial structure of economic activities

The aim of the second stage is twofold. First of all, it aims to highlight whether the spatial characteristics of the TTWAs influence commuting behaviour. Secondly, it is meant to compare if the effect of each characteristic is different considering as dependent variable the distance decay gradient or the average commuting distance.

According to the correlation among explanatory variables reported in Table 4, some of the variables originally listed in Table 1 have been excluded from the model. In particular, the employment density (*Emp.Dens.*) shows correlation with two of the main variables included in the model. Indeed, it shows a high positive correlation with the urbanization economies (*Urb.Eco.*), mostly because most of the job places are located in urban municipalities. Moreover, it is also slightly negatively correlated to polycentricity (*Polycent.*), in accordance with the definition of polycentric areas. In addition, the employment density displays a severe correlation both with the number of car accidents (*Accidents*), and the number of kms of roads per inhabitant (*Congest.*). Finally, the number of car accidents is highly correlated with the km of roads per inhabitant, as expected. For these reasons, both the employment density and the number of car accidents per km^2 have been excluded from the model specification.

Variab.	Polycent.	Job-H	Urb.Eco.	Loc.Eco.	Emp.Dens.	Roads	House	Acc.	Cong.	Ter.Educ.
Polycent.	1.000									
Job-Hous.	-0.276	1.000								
Urb.Eco.	-0.327	0.201	1.000							
Loc.Eco.	0.061	0.043	0.096	1.000						
Emp.Dens.	-0.172	0.095	0.610	0.016	1.000					
Roads	-0.127	0.112	0.258	-0.023	0.303	1.000				
House own.	0.131	0.077	-0.070	0.234	-0.242	-0.110	1.000			
Accidents	-0.070	-0.055	0.232	0.040	0.328	0.082	-0.267	1.000		
Congest.	0.057	0.000	-0.357	-0.147	-0.415	-0.008	0.233	-0.488	1.000	
Ter.Educ.	-0.260	0.250	0.460	-0.141	0.362	0.204	-0.001	0.031	0.035	1.000

Table 4: Cross-correlation table of the explanatory variables.

Two main sets of models have been estimated. In Table 5, Models 1 and 2 refer to the effect that spatial characteristics have on commuting behaviour measured using the distance decay gradient.

Instead, Models 4 and 5 estimate the effect of the same spatial characteristics on commuting behaviour measured as average commuting distance. In Table A3 in the Appendix the standardized coefficients for the Models are estimated, to better compare the magnitude of each effect[18].

Model 1 is taken as a base model, since it includes the spatial characteristics and the control variables, whereas Model 2 also includes the interaction terms between spatial characteristics and socio-economic features of the TTWAs. Looking at these models, the estimated coefficients of the main variables of interest are robust, maintaining the same sign and similar level of significance.

With respect to the spatial characteristics analysed in the literature, results show that, if the polycentricity of the TTWA increases, the absolute value of the distance decay gradient increases as well, implying that an increment in distance in polycentric areas reduces commuting flows more than in a more monocentric one[19]. This is because in more polycentric TTWAs jobs are spread across sub-centers, making more likely that workers live closer to a sub-center rich of job places. Hence, this spatial configuration leads workers to be less willing to commute long distances, confirming the predictions of the monocentric model. On the contrary, within monocentric areas most jobs are located in the CBD, forcing workers in commuting longer distances (Boarnet, 1994; Cervero, 1996; Glaeser and Kahn, 2004).

[18] To obtain standardized coefficients reported in Table A3 both the dependent variable and the exogenous ones have been standardized by subtracting the mean and dividing by the standard deviation. Hence, the estimated regression coefficients give information about the change in the dependent variable due to an increase of one standard deviation of the exogenous variables.

[19] Recall that the distance decay gradient of a spatial interaction model, as the one estimated in the first step, is the slope of the relationship between flow and distance and, therefore, it is supposed to be negative. The dependent variable in Models 1 and 2 of Table 5 is the absolute value of the distance decay gradient, hence a positive estimates describes that an increment in the exogenous variable is associated to a steeper function between commuting flows and distance.

Dependent variable	Model 1 γ	Model 2 γ	Model 3 Av. Dist.	Model 4 Av. Dist.
Polycentricity	0.504**	0.488**	5.433***	4.938***
	(0.23)	(0.22)	(1.11)	(1.07)
Job-Housing Imbalance	-0.504***	-0.545***	4.360***	4.322***
	(0.15)	(0.13)	(0.64)	(0.64)
Urbanization Eco.	-0.223***	-0.261***	-0.277	-0.349
	(0.06)	(0.05)	(0.26)	(0.28)
Localization Eco.	-0.518***	-0.548***	-1.225	-1.203
	(0.15)	(0.14)	(0.69)	(0.66)
Road Supply	-0.232*	-0.206*	-1.708***	-1.654***
	(0.12)	(0.11)	(0.35)	(0.36)
Percentage of house	-0.0137***	-0.0153***	-0.0354	-0.0346
ownership	(0.00)	(0.00)	(0.02)	(0.02)
Congestion	0.341***	0.318***	0.548	0.513
	(0.10)	(0.10)	(0.39)	(0.38)
Share of tertiary	-0.827	0.164	16.87***	17.97***
education	(0.69)	(0.67)	(3.68)	(4.41)
Urbanization × Share of		-1.758**		-0.496
tertiary education		(0.74)		(4.48)
Polycentricity × Share of		-5.833*		-29.86*
agri. and man. Empl.		(2.91)		(13.53)
Polycentricity × Share of		-0.0906*		-23.19
public sector Empl.		(4.26)		(18.78)
Regional Dummies	yes	yes	yes	yes
Constant	2.540***	2.554***	3.775*	3.652*
	(0.42)	(0.41)	(1.83)	(1.85)
Observations	475	475	475	475
R^2	0.674	0.684	0.584	0.590
Adjusted R^2	0.654	0.662	0.559	0.562

Standard errors in parentheses
*p<0.05, **p<0.01, ***p<0.001

Table 5: Weighted Least Squares estimation results.

However, interesting insights are shown by the interaction terms between polycentricity and the structure of the local economy, measured with the share of employment in manufacturing (and agriculture) and the share of employment in the public sector. The interaction involving the share of manufacturing employment in the TTWA is statistically significant and shows that the effect of polycentricity is reduced if the share of manufacturing workers in the

TTWA increases. Estimates show that workers of the manufacturing industry are less sensitive to increments in commuting distances with respect to workers of the services sector, taken as reference category. This result could be due to the fact that manufacturing activities need space for their plants and, therefore, even in a polycentric environment tend to be clustered, emulating for those workers the effect that a monocentric configuration would have. In addition, these kinds of economic activities require specialized workers that might live far away from the plants. Also, commuters belonging to the public sector show a similar commuting behaviour. It might be either due to a spatial reason or to a cultural one. The former is that public sector's activities tend to be clustered, whereas the latter is that Italian workers may appreciate to have a public-sector job, seen as more guaranteed that other job positions, and, hence, are willing to a longer commute for it.

In the literature, job-housing imbalance has always been recognized as one of the determinants of longer commute trips. Our results are in line with these predictions, since TTWAs with higher uneven distribution of jobs places and households are associated with a lower reduction of commuting flows related to increments in commuting distance.

Concerning the effect of the agglomeration economies on commuting behaviour, the results show that they display a significant effect, both in the form of urbanization and localization economies. In particular, urbanization economies as well as localization economies have the effect of reducing the absolute value of the distance decay gradient. This means that in TTWAs where the share of employment located in urban municipalities is high, as well as in TTWAs with a high level of industrial specialization, the reduction of commuting flows due to increments in distance is lower than in TTWAs with jobs mostly located outside the urban areas and with a low level of specialization. This result finds a possible explanation in the fact that, if a TTWA is characterized by high level of sectorial specialization, firms need to hire specialized workers that do not live close to the plants. The effect found for the urbanization economies also suggests that, in areas where most of the jobs are located in urban municipalities, workers tend to be less sensitive in increments in commuting distance, especially if the level of tertiary educated workers increases in the TTWA, as suggested by the interaction term. Indeed, since most of the high skilled jobs are located in the urban areas, those high skilled workers that live outside urban municipalities are willing to commute more in order to exploit their skills.

Finally, also the control variables show the expected effects on commuting behaviour. The transport infrastructure supply shows that in TTWAs with higher supply of transport infrastructure the absolute value of the distance decay gradient tends to be lower, implying that an increase in the commuting distance reduce commuting flows less than in areas with a poor supply of infrastructures. The same effect takes place in TTWAs with a high percentage of workers that own the house where they live, showing that the relocation frictions of the housing markets lead workers to be less willing to commute longer distances. Also, higher willingness to commute is associated with higher educated workers, whereas it is reduced if the level of congestion in the TTWA increases.

Comparing the magnitude of the effects of each spatial characteristics using standardized estimates reported in Table A3 in the Appendix, it can be seen that both the distribution of jobs with respect to residential areas and the urbanization economies seem to be the most relevant spatial attributes that affects the distance decay gradient.

Looking at Model 3 and 4 reported in Table 5, which use the average commuting distance as measure of commuting behaviour, some different results could be found. The most relevant one is that, according to the estimates, the average commuting distance increases in more polycentric areas with respect to monocentric one. On the contrary, as previously highlighted, in Model 2, the estimated coefficient for the effect of polycentricity on the distance decay gradient describes that the decrease of commuting flows due to increases in distance is higher in polycentric areas. This discrepancy is due to the fact that the outcome of commuting (i.e. the commuting distance) does not give information either about what commuters would do in a different spatial configuration or about the number of workers that, due to increments in distance decide to leave (or refuse) a job. On the contrary, those effects are disentangled using the distance decay gradient, that highlights the sensitivity of commuters with respect to the distance in different spatial settings.

In addition, the average commuting distance seems not to catch the effects of relevant spatial characteristics of the TTWA and provides only the effects of the more standard ones. The effect of road supply seems contradictory since the average distance decreases if the kms of road per km^2 increases. An explanation of this result is that the average commuting distance clearly suffers of the Modifiable Areal Unit Problem, that leads the results to change if the same analysis is performed for the same data but with different geographical aggregation. Hence, the average commuting distance is influenced by the surfaces in km^2 of the urban areas because of construction, and this makes the measure sensitive to all the spatial characteristics that involve the surfaces of the area in their computation (Wong, 2004).

4. Conclusions and discussions

The aim of the paper is to highlight which are the spatial characteristics of the labour market that mostly affect commuting behaviour. The topic has been explored using the methodology proposed by Melo et al. (2012), where the distance decay gradient of a spatial interaction model is used as measure of commuting behaviour instead of the more commonly used commuting distance. Here it has been proved that, by looking at the distance decay gradient, it is possible to describe commuting behaviour conditional to spatial structure of the areas involved in the journey. Moreover, two hypotheses concerning the influence that socio-economic features have on the relationship between the spatial characteristics and commuting behaviour are tested.

The results show that the spatial configuration of the area where commuting takes place has a strong impact on commuting behaviour, giving relevant policy insights. Indeed, previous literature has emphasized that commuting behaviour is mainly due to personal characteristics (Gutiérrez-i-Puigarnau and van Ommeren, 2010), implying that, to reduce externalities due to daily trips to work, the best strategy is to give individual incentives to change personal behaviour. However, the present analysis suggests that there is a wider choice of policy interventions. If the frictions due to personal characteristics are difficult to change, the spatial structure of the environment is, to some extent, easier to manipulate. According to the estimated results, policies acting on spatial characteristics of the labour market would obtain the same effect of some policies related to personal characteristics of the workers, at least partially. Finally, it has been shown that researches only based on the average commuting distances are not sufficient to disentangle all the effects that the spatial characteristics have on commuting behaviour.

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Appendix

Average value of the estimated distance decay gradient models

	Mean	**Std. Dev.**	**Min.**	**Max.**
OLS	-2.789	0.924	-6.037	-0.759
Poisson	-4.039	1.08	-8.622	-1.377

Table A1: Average value of the estimated distance decay gradient using travel time.

As it can be seen from Table A1, the estimated distance decay gradient using travel time are not as robust as the ones estimated with travel distance even if, as reported in Table A2, the correlations between average estimates are sufficiently high. The correlation between OLS estimates is higher than the one between Poisson estimates, because, since the OLS does not consider the observation with zero flows, it suffers less of the fact that the zero-flow travel time has been predicted.

	Distance OLS	Distance Poisson	Time OLS	Time Poisson
Distance OLS	1.00			
Distance Poisson	0.74	1.00		
Time OLS	0.68	0.36	1.00	
Time Poisson	0.50	0.42	0.69	1.00

Table A2: Correlation table of the distance decay gradient estimated using travel distance and travel time.

Other results

In Table A3 the standardized coefficients of the estimated models are reported.

Dependent variable	Model 1 γ	Model 2 γ	Model 3 Av. Dist.	Model 4 Av. Dist.
Polycentricity	0.084**	0.082**	0.253***	0.230***
	(0.23)	(0.22)	(1.11)	(1.07)
Job-Housing Imbalance	-0.184***	-0.199***	0.443***	0.439***
	(0.15)	(0.13)	(0.64)	(0.64)
Urbanization Eco.	-0.190***	-0.223***	-0.066	-0.083
	(0.06)	(0.05)	(0.26)	(0.28)
Localization Eco.	-0.143***	-0.151***	-0.094	-0.093
	(0.15)	(0.14)	(0.69)	(0.66)
Road Supply	-0.113	-0.101	-0.233***	-0.225***
	(0.12)	(0.11)	(0.35)	(0.36)
Percentage of house ownership	-0.172*** (0.00)	-0.192*** (0.00)	-0.124 (0.02)	-0.121 (0.02)
Congestion	0.181***	0.169***	0.081	0.076
	(0.10)	(0.10)	(0.39)	(0.38)
Share of tertiary education	-0.061 (0.69)	0.012 (0.67)	0.348*** (3.68)	0.371*** (4.41)
Urbanization × Share of tertiary education		-0.095* (0.74)		-0.007 (4.48)
Polycentricity × Share of agri. and man. Empl.		-0.085* (3.03)		-0.121* (13.53)
Polycentricity × Share of public sector Empl.		-0.001 (4.26)		-0.066 (18.78)
Regional Dummies	yes	yes	yes	yes
Observations	475	475	475	475
R^2	0.674	0.684	0.584	0.590
Adjusted R^2	0.654	0.662	0.559	0.562

Standardized beta coefficients; Standard errors in parentheses
*$p<0.05$, **$p<0.01$, ***$p<0.001$

Table A3: Standardized estimated coefficients of the main models.

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