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Commuting in Europe: An Inter-regional Analysis on its Determinants and Spatial Effects

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Summary

Commuting shapes countless everyday-lives around the world, with dynamics varying from city to regional and cross regional level. Taking as reference the free-movement EU-28 area (plus Switzerland and Norway), the analysis considers a total sample of 195 NUTS2 regions over the decade 2007-2017 to depict regional cross-border dynamics, thus including the impacts of the 2008 financial crisis. The tested presence of spatial interactions among regions leads to the adoption of the Spatial Durbin Model in a panel context, thus including fixed effects in order to eliminate any time influence on variables as well as any regional idiosyncrasy (i.e. cultural, institutional etc.). The outcoming analysis highlights the potentiality of temporary contracts in preserving jobs during crisis, as they offer a flexible tool for employment adjustments. Moreover, the regional specialization in the knowledge sector is found to be an important attractor of external workers as well as a relatively effective retaining factor of the domestic labour force. But there are also other factors affecting mobility. For instance, the perceived commuting distance significantly depends on the time needed to reach the corresponding workplace and this study finds that the more diffused is the transportation system (in terms of highways' density) the higher the commuting outflow. A similar impact is found with respect to housing costs, that is the cheaper is the relative house price of the region of residence with respect to the surrounding territories, the more travel-to-work becomes an attractive option, even in its extend of long-distance commute. Finally, a last strong push factor of mobility is found in the lack job opportunities, here expressed as the unemployment rate differential for each single territory with respect to its surroundings. Indeed, the higher the lack of job opportunities in the domestic market with respect to its neighbours, the higher the share of workers that will try to seek their fortune crossing the regional border.

Keywords: Cross-border Commuting Outflows, Regional Economics, Panel Analysis, Fixed Effects, Spatial Econometrics

JEL Classification: C51, C54, C55, J21, J61, J62, R11, R12

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Commuting in Europe: An Inter-regional analysis on its determinants and spatial effects

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Abstract

Commuting shapes countless everyday-lives around the world, with dynamics varying from city to regional and cross regional level. Taking as reference the free-movement EU-28 area (plus Switzerland and Norway), the analysis considers a total sample of 195 NUTS2 regions over the decade 2007-2017 to depict regional cross-border dynamics, thus including the impacts of the 2008 financial crisis. The tested presence of spatial interactions among regions leads to the adoption of the Spatial Durbin Model in a panel context, thus including fixed effects in order to eliminate any time influence on variables as well as any regional idiosyncrasy (i.e. cultural, institutional etc.). The outcoming analysis highlights the potentiality of temporary contracts in preserving jobs during crisis, as they offer a flexible tool for employment adjustments. Moreover, the regional specialization in the knowledge sector is found to be an important attractor of external workers as well as a relatively effective retaining factor of the domestic labour force. But there are also other factors affecting mobility. For instance, the perceived commuting distance significantly depends on the time needed to reach the corresponding workplace and this study finds that the more diffused is the transportation system (in terms of highways' density) the higher the commuting outflow. A similar impact is found with respect to housing costs, that is the cheaper is the relative house price of the region of residence with respect to the surrounding territories, the more travel-to-work becomes an attractive option, even in its extend of long-distance commute. Finally, a last strong push factor of mobility is found in the lack job opportunities, here expressed as the unemployment rate differential for each single territory with respect to its surroundings. Indeed, the higher the lack of job opportunities in the domestic market with respect to its neighbours, the higher the share of workers that will try to seek their fortune crossing the regional border.

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1. Introduction

In Europe, starting from the 1950s economic boom, the gradual development of an extended transport and communication system first and the consequent diffusion of digital technologies have characterized the shift towards the post-industrial society we live in today. This has redefined the relationship between workplace and home for a countless number of people. At personal level, the decision to commute for longer time or to reach more distant destinations depends on both individual attributes (i.e. gender, age and attained education level) as well as on job characteristics (such as being employed in particular industries or on temporary contracts) and personal judgments (i.e. commuting as factor causing stress vs commuting as synonymous of better job opportunities).

With respect to the former, gender plays a fundamental role on mobility (MacDonald, 1999; McLafferty & Preston, 1997; Paull, 2008; Sandow & Westin, 2010). According to the literature, less restrictive childcare responsibilities as well as milder household obligations (Dex, Clark, & Taylor, 1995 and Grieco, Pickup, & Whipp, 1989; Turner & Niemeier, 1997) push men to travel more and for longer time than women. Indeed, ladies' lower commuting times might be related to a monetary gap existing between males and females salaries (Madden,1981) which seems to be further deepened by motherhood (Booth & van Ours, 2008; Waldfogel, 2007) as mothers seems to be more likely to work part-time and earn less than the other women while the reverse holds for men, with fathers earning more than non-fathers. Age is another important determinant in commuting decisions and according to previous research, older workers have longer working experience as well as stronger workplace attachment and these would lower their willingness to accept longer distance jobs (Booth, Francesconi & Garcia-Serrano, 1999; Topel & Ward, 1992). However, older workers are also expected to be home-owners and have family obligations to take care of, which make the cost of permanent relocation much higher compared to young workers (Romani, Surinach, & Artis, 2003; van Ham, Mulder & Hooimeijer, 2001) and this could increase their propensity to commute. Finally, a last important driver of individual mobility is education. That is, literature finds more educated workers to be relatively more likely to find fulfilling jobs when travelling further, at least compared to lower educated workers (Groot, de Groot and Veneri,2012; van Ham et al.,2001; van Ham & Hooimeijer, 2009). In addition, high-skilled workers are, on average, paid more than low-skilled workers so they can afford higher housing prices and live in residential and low-dense populated suburbs, thus commuting more and for longer time.

Moving to job characteristics, a first important driver of mobility is represented by the working status. Indeed, several studies have highlighted the fact that self-employed individuals tend to minimize their commuting distance as industries at high concentration of self-employment are also more spatially decentralized with respect to those concentrated on wage-employment, with employees usually accepting more distant jobs (Giuliano,1998; Romani et al.,2003; Stutzer and Frey,2008). Besides, wage rates do also influence workplace mobility, especially if combined to individuals' housing situation. That is, according to McQuaid & Chen (2011), job changes occurring to lower-paid workers are more likely to increase their commuting distances due to the impossibility to afford more central housing. Considering the type of contract a worker is hired on, then full-time employed individuals are found to be more likely to commute for longer time (Hong, Lee, Mc Donald,2002; McQuaid, Chen,2011) and the reasons behind are many. First, part-time occupations present higher turnover rates and second, workers are usually younger, lower-paid and/or female and these are all factors that have been previously addressed to shorter commutes (Salmieri,2009; Giuliano,1998; Dijst&Schwanen, 2002). Another important aspect left to consider deals with the occupational condition of permanent or of temporary employment. According to previous research (Rouwendal and Meijer,2001; Parenti & Tealdi,2015), temporary workers usually feel more uncertain with regards to the future of their employment and this can entangle them to their current residence, even if it implies longer commutes.

From this brief overview, it clearly emerges how mobility choices are indeed complex decisions that individuals made by considering different aspects related to their jobs as well as their socio-economic characteristics. Recognizing these factors is also important to study workplace mobility under a broader prospective, which starts from the individual level and moves to the regional case in order to understand how aggregate commuting flows can shape the socio-economic structure of entire geographic areas, either in terms of infrastructures (and in particular through the development of new transportation and communication systems) or in terms of urbanization, through the creation and extension of cities and metropolitan districts[3]. In order to understand commuting outflows dynamics, the regional dimension has been chosen to be the best compromise between the need of accurate estimates and good-quality data. Consequently, the study will consider the cross-border commuting dynamics occurring among 195 European regions over the decade 2007-2017.

In these circumstances, the spatial context is an important aspect to consider, as workers decide whether or not to commute by considering both domestic and external regional characteristics. For instance, a scarce availability of job opportunities in the local market pushes workers to cross regional borders in order to escape the resulting underemployment from spatial mismatch (Preston & McLafferty, 1999; van Ham et al.,2001; Reggiani et all.,2011). Furthermore, regional disparities may occur not only opportunity-wise but also in monetary terms (Bentivogli & Pagano,2003;

[3] According to the European Commission (2019) the majority of the global population (55%) already live in urban areas and the proportion is expected to rise to 68% by 2050 as reported by the United Nation Department of Economic and Social Affairs (2018).

Muellbauer & Cameron,1998), as areas of relatively higher wage rates are usually able to attract individuals from larger territories with respect to the average (Reggiani et al.2011). Nevertheless, it is not infrequent for these regions to have prohibitive house prices (Romani et al., 2003) and this can make travel-to-work a more attractive option to migration, even in its long-distance extend (Allen,2014; Muellbauer & Cameron, 1998; Reitsma & Vergoossen, 1988). Yet, at aggregate level, another aspect of job uncertainty that induces workers to look for external job opportunities is represented by the massive usage of temporary contracts in the local labour market (Parenti & Tealdi,2019) which characterizes territories specialized in specific economic sectors of seasonal nature, such as agriculture and tourism (Gagliarducci,2005). Finally, a last fundamental aspect affecting aggregate commuting decisions is given by the quality of infrastructures (with particular focus on transport and communication), which can alterate the perceived travelling distance (Zhu et al.,2017) .

As shown in the previous paragraph, studies on aggregate mobility flows should not be restricted to the sole identification of what drives workers willingness to commute but rather include a spatial analysis that can indicate whether decisions taken in a unit (or region, in this case) have an impact on the surrounding spatial context. Nonetheless, the existing literature on workplace mobility seems to underestimate the importance of spatial econometrics, thus neglecting some meaningful and realistic insights on the occurring dynamics. Considering this lack as an opportunity, it will be interesting to combine traditional research techniques to spatial methods in order to understand what individual and macroeconomic drivers affect regional commuting outflows when considering spatial inter-dependence among territories.

Hence, the paper is organized as follows. Section 2 offers a description of the dataset, with additional observations on selected descriptive statistics while Section 3 and 4 present the methodology used in the analysis, first specifying the model and then considering the additional spatial framework. Moving to the empirical part, Section 5 tests for the existence of spatial patterns in the sample and then applies the Spatial Durbin Model to the data, including time fixed effects. In light of the outcoming results, Section 6 concludes with an overview on the major findings and suggests some selected policy advices.

2. Data and Descriptive Statistics

2.1 Data

In this study, the main data source is represented by the European Union Labour Force Survey (EU-LFS) that is a large households sample survey on the labour participation of people aged 15 and over. It covers the 28 Member States of the European Union[4] plus three members of the European Free Trade Association (EFTA) namely Iceland, Norway and Switzerland. The data collection is available from year 1983 onwards, as surveys are conducted by national statistics offices and then processed by Eurostat, which harmonizes data at European level.

The survey provides both demographics and socio-economic information at individual level (sex, education level, age, type of household) with particular focus on employment and job characteristics (e.g. working status, job category, full-time/part-time occupation, permanent or fixed term contract and job tenure). In addition, each interviewee has to provide two fundamental pieces of information for this study, namely the NUTS codes[5] of both his/her current residence and workplace so that work mobility (expressed as commuting) is determined whenever the NUTS codes differ. Starting from information in LFS, the outcoming dataset is enriched by other external contextual variables, namely the regional Unemployment Rate (Eurostat), the National House Price Index[6] (Bank of International Settlements) and two regional indexes related to Road and Railway Network Quality (Eurostat).

The initial idea to include only NUTS2 areas (i.e. regional administrative units) had to be abandoned due to the scarce availability of good quality data over years. At the end, different aggregation levels were considered (i.e. United Kingdom, Austria and Germany have been aggregated at NUTS1 whereas the Netherlands, Switzerland and Lithuania have been considered as a unique territory at NUTS0 level). Yet, some territories have been intentionally excluded from the analysis as they showed exclusively internal commuting (with the consequent risk to bias the estimates) or changes of internal borders[7] as well as unreliable weighting design (i.e. the Greek

[4]That is EU27 plus the UK

[5]The NUTS (Nomenclature of Territorial Units for Statistics) classification is a geocode standard for referencing the subdivisions of countries for statistical purposes. The standard, adopted in 2003, is developed and regulated by the European Union, thus providing detailed information only for EU members as well as Norway and Switzerland. For each EU country, a hierarchy of three NUTS levels is established by Eurostat in agreement with each member state however the subdivisions of some levels do not necessarily correspond to administrative divisions within countries. In smaller states, where the entire country would be placed on the NUTS 2 or even NUTS 3 level (ex. Luxembourg), the regions at levels 1, 2 and 3 are identical to each other (and also to the entire country), but are coded with the appropriate length codes levels 1, 2 and 3.

[6] The base year for the National House Price Index is 2010.

[7] For the majority of these cases (Cyprus, Malta, ES70-Canarias and Iceland) the exclusive internal commuting can be explained by the peripheric position that these countries have within the European continent while Slovenia was excluded because of an internal boundaries change occurred in 2010. Other omitted territories are EU member states' overseas territories (i.e. French territories in Africa).

case). Consequently, the final choice considers the 2007-2017 decade in order to preserve the opportunity to highlight the effects of the 2008 financial crisis. From here, only individuals having an active working status (following the ILOSTAT definition[8]) will be weighted and aggregated at the designated NUTS level.

2.2 Commuting in Europe

Before moving to the analytical part, it might be useful to take a closer look at the dataset through a descriptive summary. That is, starting from the LFS micro-data and considering only employed individuals[9], then the commuting outflows are constructed as the annual regional share of inter-regional commuters, written as

$$Shr\_Commt_{i,t} = \sum_{\mathrm{r}=1}^{\mathrm{R}} \frac{\omega_{\mathrm{r}}}{\mathrm{W}} d_{\mathrm{r,t}}{}^{c} \quad \mathbf{(1)}$$

where every working resident r is assigned to a dummy variable $d_r{}^c \begin{cases} 1\ workplace\ \neq\ residence \\ 0\ \qquad otherwise \end{cases}$ that catches the effective cross-border mobility and ω_r is the unique individual design weight for which $W = \sum_1^R \omega_r$ is the regional sum of weights related to the $r = 1, \dots, R$ working individuals. Hence, for a given year t then the share of cross-border workers in the region i is given by the weighted mean value $Shr\_Commt_{i,t}$.

A first insight on cross-border dynamics is given by Figure 1 below, where the yearly sample average (grey line) is plotted over time. From 2012 onwards, the steep positive slope indicates that cross-border commuting is gradually becoming more popular in Europe, after the initial erratic trend registered during crisis years (2009-2012). With respect to time, the dotted red line corresponds to the temporal mean value of 5.9% (C.I.: 5.8 - 6.0 %), that is the average proportion of regional cross border commuters with respect to the total number of employed individuals (either in self or in wage employment) during the period considered.

[8] Persons employed in the sense of the ILO are those who worked for any amount of time, if only for one hour, in the course of the reference week. This notion is different from that of employment in the sense of the population census, which concerns persons having declared they had a job on the census form. The notion of employment in the sense of the ILO is broader than that in the sense of the population census as some people may consider that occasional jobs are not worth declaring in the census.
[9] Hence following the ILOSTAT definition

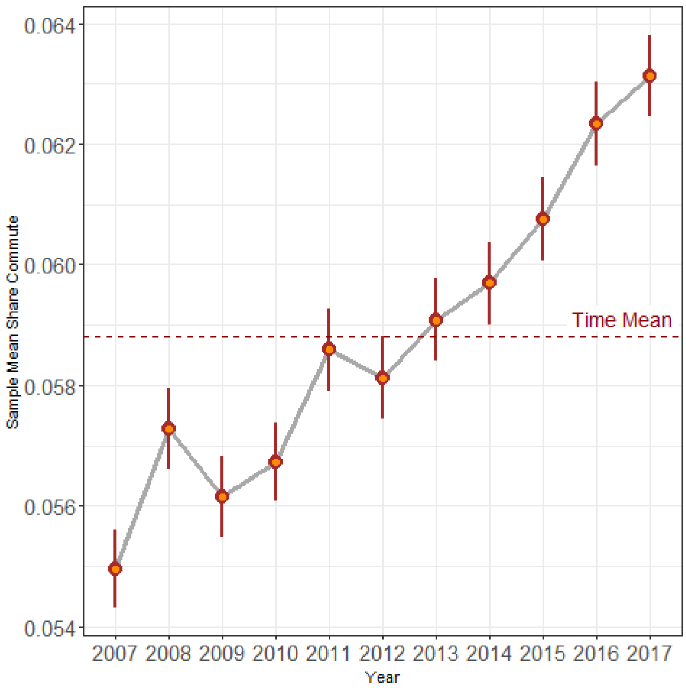


Figure 1- 95% C.I. Regional Cross-border Commuting in EU regions over 2007-2017

Other useful observations are gathered by looking at the cross-border mobility distribution in Figure 2.a and Figure 2.b below, for initial and final years respectively. A first interesting observation comes from a comparison on the two maps that shows how, in general, regions seem to maintain their initial position with respect to the overall sample distribution. Nonetheless, the positive time trend previously spotted in Figure 1 is here confirmed by the increase in the quartile values, with the only exception of the last one that remains constant over time. Moreover, first in the maps and even more clearly in the dot plots, several satellite regions[10] present many of the highest cross-border shares, either comparing them to National or to European averages[11]. Throughout the decade, the regions with the highest proportion of cross-border commuters are those surrounding the city of Brussels (namely the Province Brabant-Wallon and the Province Vlaams-Brabant) with shares over 40% (confirming the results of the European Commission,2015).

[10] Here defined as territories of close proximity to the corresponding Capital City NUTS2

[11] To cite the most important: DE40-Brandeburg (surrounding area of Berlin), BE31- Province Brabant-Wallon and BE24- Province Vlaams-Brabant (surrounding area of Brussels), DK02-Zealand (surrounding area of Copenhagen), ES42-Castilla-La Mancha (surrounding area of Madrid), UKH0-East of England (surrounding area of London), FR22-Picardie (surrounding area of Paris) and CZ02-Central Bohemia Region (surrounding area of Prague).

Figure 2.a- Regional Cross-border Commuting Distribution 2007

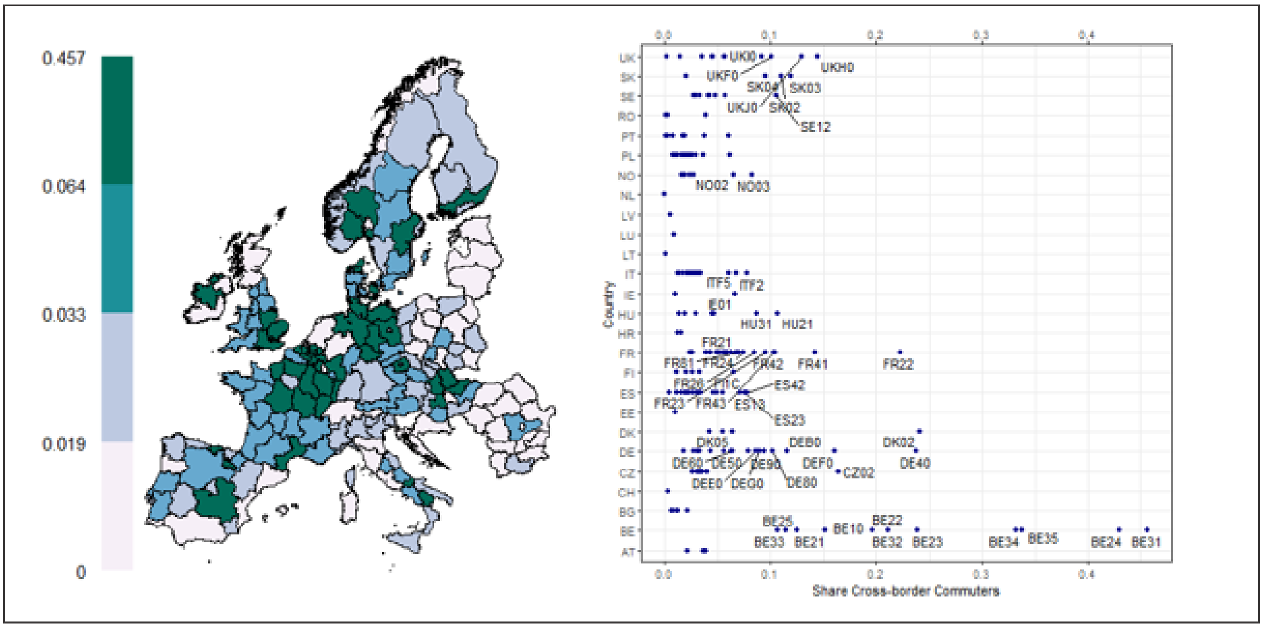
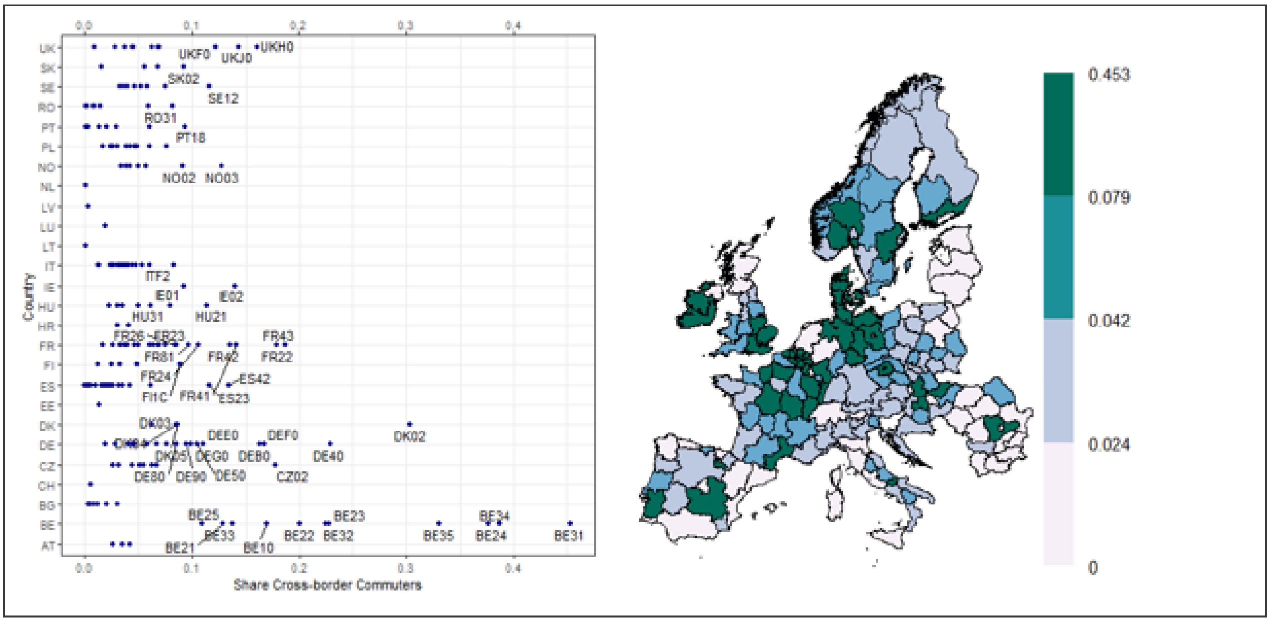


Figure 2.b- Regional Cross-border Commuting Distribution 2017



3. The Model

The deriving linear econometric model can be written as

$$Shr\_Commt_{i,t} = \alpha + X_{i,t}\beta + \varepsilon_{i,t} \quad (\mathbf{2})$$

where the outcome variable $Shr\_Commt_{i,t}$ is defined by a constant term α , a set of variables X (i.e. *regressors*) and by the error term $\varepsilon_{i,t}$, assumed to be normally distributed or $\varepsilon \sim N(0;\sigma^2)\ \forall\, i,t.$ In the following sections, a full description of the set (X) will clarify the included explanatory variables, which are grouped into three main categories: the regional *socio-demographic* and *job* related characteristics, derived via aggregation of LFS microdata, and other *specific* regional features coming from external data.

3.1 Regional Characteristics based on Aggregated Eurostat LFS

Individual Socio-Demographic Variables

Regional Share of males: Regional share of active male population. According to the literature at individual level (MacDonald, 1999; McLafferty & Preston, 1997; Sandow & Westin, 2010), there is evidence addressing higher propensity to long-distance commutes to male workers rather than women and this implies an expected positive coefficient also at regional level.

Regional Share of cohabitating partners: Share of cohabitating couples at regional level. This variable is gained from the individual dummy that switches on whenever the interviewee shares the residence with his/her partner and it is preferred to the Martial Status as it considers all couples living together (being or being not married). Previous studies found that dual-commuters households do not trade-off commute distance but they rather try to decrease the joint travel distance (Flowerdew, 1992; Green, 1997) however, ELFS does not allow to track partners' working status and a more general assumption in favor of a positive effect on regional commuting outflows is expected.

Regional Share of households with in-house offspring: Regional share of households with children living at home (not controlling for their age) gained from the individual dummy capturing offspring in-house presence for those who are parents. The dataset also provides for a variable that identifies the number of 00-14 years old persons in the household, which might be useful for a robustness check. According to the literature (Crane & Takahashi, 2009) the birth of a child may result in a household moving to suburban areas because of their better life quality (i.e. presence of green areas and parks, schooling quality etc.) with a corresponding increase in commuting time, hence a positive sign is here expected.

Regional Population Distribution by Age: Shares of regional labour force by four age-classes, namely individuals between 15 and *2*4 years old, 25-34, 35-49 and 50 and over. These groups are gained by the individual information on age. According to previous research (Romani, Surinach & Artis,2003; van Ham,Mulder & Hooimeijer, 2001) older workers are expected to be home-owners and have family obligations to take care of, hence an increasing propensity to commute is expected for greater shares of regional elderly workers.

Regional Population Distribution by Education: Shares of regional labour force by educational attainment where the individual variable indicates the highest ISCED[12] level achieved and the regional aggregation computes shares of residents being at Primary (elementary schooling or ISCED 1), Secondary (lower and upper secondary schooling or ISCED 2-3) and Tertiary level (post-secondary schooling or ISCED 4-6). Here, the expected sign is positive for an increasing education level, or human capital (Ronald W. McQuaid, Tao Chen, 2011; Romaní, Suriñach & Artiís, 2003) thus matching with evidence at the individual level (van Ham et al.,2001; van Ham & Hooimeijer, 2009; Borsch & Supan,1990; Simpson, 1992).

3.2 2nd Group of Regional Characteristics based on Aggregated Eurostat LFS Individual Job Features

Regional Job Tenure Length: Average value of regional contracts' length based on the weighted mean of individual job tenures expressed in months. For an increasing value of the outcoming regional job tenure, a lower propensity to commute is expected. That is, following the study of van Ham et al. (2001) on individual commuting propensities, the increase of job tenure can be translated into a greater firm attachment and/or sector specialization but also into shorter time before retirement. These are all factors that would make job changes more costly, both in monetary and non-monetary terms.

Regional Share of Full-Time Contracts: Regional share of working residents in full-time occupation. Starting from the individual variable detecting full-time working activity then the

[12] The ISCED classification - International Standard Classification of Education - was developed by UNESCO in the mid-1970s and was first revised in 1997. Further reviews of schooling levels were undertaken during years. For period 2007-2017, information on education are based on ISCED 97 until 2013 and ISCED 2011 from 2014. In order to allow for comparison, the latest version (for a total of 8 levels) has been converted to ISCE 97 version (6 levels).

regional share is gained via aggregation (through the weighted average). According to the literature, Full-time occupation is considered as a further push to commute for longer time (Hong, Lee, Mc Donald,2002; McQuaid,Chen,2011) and the reasons behind are many. First, part-time turn over presents higher rates and second, workers are usually young, low-paid and/or female and these are all factors recognized to have negative influence on long-distance workplace mobility (Salmieri,2009; Giuliano,1998; Dijst & Schwanen, 2002).

Regional Share of Temporary Contracts: Regional share of temporary contracts. Following the previous full-time feature, ELFS provides also an individual question that highlights whether the interviewee is hired on a fixed-term contract and the corresponding regional value is aggregated consequently. According to previous research (Parenti & Tealdi, 2019) being on temporary contract is seen as a boost to commute for longer distances because of the uncertainty related to contract's renewal at the end of the fixed-term (a situation frequently occurring in Southern Europe, according to the European Commission, 2010).

Regional Employment Distribution by Firm size: Regional Employment distribution defined by each interviewee as the number of total employed persons in his/her firm. Given this piece of information, the regional aggregation classifies companies into Small, Medium and Large firms with cuts at 20, 50 and more than 50 employees. Following the literature on individuals, large companies seem to induce workers to travel for longer distances (Scherer, 1976). In part, this might depend on the ability of big companies to recruit from larger territories as well as the relatively higher availability of employees' payback schemes for transportation costs, especially compared to medium and small firms (Paci et al.,2007). Following the literature, a positive influence on commuting outflows is expected for increasing employment shares in large firms, although different dynamics might arise when moving from individual to regional level.

Regional Employment Distribution by Economic Sectors: Shares of regional employment by industrial sectors. Indeed, the individual sector of employment (following the NACE[13] classification) is provided in the LFS micro-data. Consequently, information on individuals are grouped into the *Primary Sector* (i.e. jobs in Agriculture and Forestry, Fishing, Mining and Quarrying industries) or into the *Secondary Sector* (i.e. jobs in Manufacturing, Electricity and Gas, Water Supply, Construction, Vehicles Repairing and Wholesale & Retail Trade activities[14]) or into the *Tertiary Sector* (the employment in Hospitality (i.e. jobs in Hotels and Restaurants, Logistic and

[13] NACE acronym (Statistical classification of economic activities in the European Communities) is used to designate the various statistical classifications of economic activities developed since 1970 in the European Union. Statistics produced on the basis of NACE are comparable at European and at world level. The use of NACE is mandatory within the European Statistical System. Here, the available information give the first level of classification (i.e. section).

[14] Unfortunately, Retail can't be identified as singular activity so that it is usually classified as part of the Tertiary sector.

Storage, Real Estate, Administration and Business Support, Public Administration, Recreation and Households Employees sectors) or, finally, into the *Knowledge sector* (i.e. jobs in Information and Communication, Education, Social Health, Finance and Consulting activities as well as Professionals such as lawyers, architects, engineers, medical practitioners etc). This last sector focuses on those industries characterized by an intensive technology and/or human capital use and its potential effect on commuting is justified by several studies that link individuals belonging to this category as more keen to commute. That is, previous research highlights a higher propensity towards mobility for specific job categories, particularly concentrated in the Knowledge sector (de Vos, van Ham et al., 2019) as well as for high skilled jobs (van Ham et al., 2001;Finland Statistical Office, 2017). However, given that the previous classification focuses on the regional work force specialization rather than on individuals' occupation, the analysis might lead to different results.

3.3 3rd Group of Regional Characteristics based on External Data

Regional Unemployment Rate Differential: Regional index that compares unemployment rates across regions. In order to get a more realistic picture, instead of including regional unemployment rates the differential measure expresses a certain region's unemployment level with respect to the average of the other ones. That is, starting from the regional unemployment rates provided by Eurostat then for every region the corresponding Unemployment Rate Differential is computed as ratio of its annual rate of unemployment over the weighted average of the unemployment rates of all the other regions (or potential destinations) where the weights are the inverse of the distance between two regions' centroids. In particular, for every region, all paired distances with the other sample units are first inverted and then row-standardised to get weights. Following the literature on the unemployment effect on work mobility (Eliasson et al., 2010;Roberts & Taylor, 2017;Crane, 1996) the relationship is expected to be positive as the lack of job opportunities is a notorious push factor towards migration in all its forms.

Regional Wage Differential: Similarly to the previous case, this Regional Index measures the income
differential based on the regional value of the Annual Compensation of Employees[15] (Eurostat). That is, the index is given by the ratio between the corresponding regional employees' compensation at the numerator and the weighted average of the employees' compensations of the

[15] Eurostat identifies the Compensation of employees (at current prices) as the total remuneration, in cash or in kind, payable by an employer to an employee in return for work done by the latter during the accounting period. Compensation of employees consists of wages and salaries, and of employers' social contributions expressed in millions of euro. Data un Switzerland (CH) are provided directly by the Helvetic National Office of Statistics.

other regions at the denominator, where the weights are derived as in the previous case. According to Reggiani et al. (2011) higher wage rates should attract workers from larger territories and be able to retain native workers.

Regional Road quality: The index is computed following Parenti et al (2019) and dividing the regional
highway length (in kilometers) by the area extension (in thousand kilometer squared) using Eurostat tables. A symmetrical measure is also available with respect to the length of the railway network so that the corresponding Railway quality index is considered for robustness checks. The effect of transport infrastructures on commuting is expected to be positive (Guirao, Campa et al., 2018).

Regional Level of Urbanisation: Following the definition of urbanization proposed by J. Makarov et al (2007), the index is here expressed as the national share of households for areas exceeding 300 individuals/km^2. Once again, data rely on Eurostat tables, even though information on Norway and Switzerland have been taken from the respective national office of statistics, due to unavailability. The expected result for the upcoming analysis considers higher propensities to commute for increasing urbanization levels (Zhu et al., 2017).

National House Price Level: The variable identifies the national yearly house price, since regional prices are not available. Data come from the International Bank of Settlement (IBS) which uses price indexes in order to capture any change in the real estate market with respect to a reference year (here 2010). Evidence is again in favour of a positive relationship with commuting, which constitutes a more attractive option instead of relocation at increasing housing costs (Allen, 2014).

4. Spatial Analysis

This study analyses commuting patterns across European regions taking into account the potential influence that units can play among each other. Spatial dependence can be seen as a special case of cross-sectional dependence where the correlation structure derives from the units arrangement in the physical space.

The initial issue faced in spatial econometrics regards how this influence can enter into a theoretical model and the solution is based on the definition of a corresponding weight matrix (or W Matrix) which assigns weights based on the intensity of the relationship between each two units, expressed as the distance between their *centroids*[16]. Once all distances are computed then the researcher assigns a design to derive the corresponding weights, here given by the general rule $w_{ij} = {}^{1}/_{d_{ij}}$ where the weighting element w_{ij} is the inverse of the distance between unit *i* and *j*. Consequently, the W Matrix for N units

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,N} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N,1} & w_{N,2} & \cdots & w_{N,N} \end{bmatrix}$$

is a positive and symmetric $N \times N$ matrix whose diagonal elements are equal to 0 by definition (namely the distance between any units with itself is set to zero). Yet, additional specifications need to be clarified in order to derive the final W matrix used throughout the analysis.

First, there is need to point out that spatial correlation (differently from time correlation) cannot be universally and uniquely determined as researchers can choose, for example, the maximum distance at which neighbouring behaviors are allowed to influence other units. In this case, the threshold assigning non-contiguity (hence reciprocal influence equal to 0) is set to 467 km, which corresponds to the first quartile in the sample distance distribution, so that every region will interact with a different number of neighbours according to its geographical position. Once the first quintile cut-off is applied, weights are further manipulated and row-standardised to get values ranging from 0 to 1, where the general standardization rule ${w_{ij}}^{s} = \frac{w_{ij}}{\sum_i w_{ij}}$ holds for every matrix row denoted by i.

[16] Throughout the analysis the distance measure will be the Great Circle distance, which implies the shortest distance between two points on a sphere. Given two points in the longitudinal-latitudinal space $A(x_1; y_1)$ and $B(x_2; y_2)$ then their distance will be $d^{e}{}_{AB} = r \times arccos^{-1}[\cos|x_1 - x_2| \cos y_1 \cos y_2 + \sin y_1 \sin y_2]$ where r = 6371 km is the radius Earth.

Once the weight matrix is computed, a next preliminary step involves the selection of statistical measures that test for the existence of spatial autocorrelation[17] among the sample units. In this case, the spatial influence among European territories is considered first with respect to its overall existence and then for the presence of local clusters, thanks to implementation of the Moran's Indexes.

In particular, the test for the overall existence of spatial interdependence is given by the Global Moran's Index, that is

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S \sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (\mathbf{3})$$

where N stands for the number of units and $S = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$ with w_{ij} being the generic element of the Spatial Weight Matrix that measures the distance (or connectivity) between any paired *ij* regions[18]. The value of I ranges from -1 (perfect dispersion) to +1 (perfect correlation) where 0 indicates a random spatial pattern. Interestingly, Equation (**3**) is equivalent to write the formula of the β coefficient in the linear regression[19] of *Wx* on *x* (where *W* is the weight matrix and *x* is the observed variable) measured in means deviation, namely $\widetilde{Wx} = \beta \tilde{x}$[20] (following the notation of Rios,2018 throughout the section). Once the index I is computed, the Z-statistic can be used in order to calculate the p-value that attributes significance to the spotted spatial pattern.

The second measure adopted to catch cross-regional clusters belongs to the family of Local Indicators of Spatial Autocorrelation (LISA) whose aim is to detect local clusters and/or spatial outliers among the sample units, where the formers identify contiguous regions of similar behaviour (i.e. *hot spots* for high index values and *cold spots* otherwise). Conversely, a spatial outlier is a unit with reversed orientation with respect to its neighbours. The index choce for the analysis is the Local Moran's I, which can be written as

$$I_i = \frac{(x_i - \bar{x}) \sum_{j=1, j \neq i}^{n} w_{ij} (x_j - \bar{x})}{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2} \text{ for all } i = 1, \ldots, \text{n} \quad (\mathbf{4})$$

Here, the sign of I_i is determined by the numerator of Equation (**4**), which is positive when both *i* and its surroundings lie simultaneously above or below the average value of *x*. On the contrary, the sign of the numerator is negative when *i* and its neighbours present different behaviours with

[17] Where the auto- prefix suggests spatial interaction of the same variable (or attribute) in two different locations.
[18] Notice the if the weight matrix is row-standardized than S=n so that $I = \frac{\sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$, or in matrix form $I = \frac{z' W z}{z' z}$ where $z = x - \bar{x}$.
[19] Recalling from OLS coefficients formula that $\hat{\beta}_{OLS} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$.
[20] Where the tilde represents the notation in deviation terms.

respect to the average value of *x*. The denominator is a simple standardization of the upper cross-product by the variance of variable *x*. As before, also Equation (**4**) can be tested for its statistical significance with the Z-statistic.

Applying these two measures on the data, spatial autocorrelation is confirmed both at global and local levels[21] hence spatial effects should be included in the model. Within the spatial framework, econometrics mainly focuses on three different kinds of interactions: the *endogenous effects*, which occur when the behavior of a unit is driven (at least partially) by the surrounding outcome variables (*Wy*); the *exogenous effects*, where the source of influence on the response variable of a unit comes from the explanatory variables of its neighbours (*Wx*) and the *spatial error effects*, where the source of influence lies in the omitted part of the model (*Wu*).

Generally, when dialing with spatial analysis there are no common rules to follow and in order to derive which specification better represents the data, it might be useful to start with a certain model and test whether other interactions occur. In the commuting analysis, the starting point is chosen to be the Spatial Durbin Model including both endogenous and exogenous spatial autocorrelation terms as it sounds reasonable to assume that cross-border commuting outflows may depend not only on the own exogenous variables of a region (such as its share of temporary contracts or age distribution, the residents' education structure etc.) but also on the corresponding exogenous variables and commuting outflows of its surroundings.

Thus, considering both spatial effects, then it holds that

$$y \;=\; \rho Wy \;+ X\beta + WX\theta + \varepsilon \quad (\mathbf{5})$$

whose reduced form is

$$y = (I - \rho W)^{-1}(X\beta + WX\theta) + (I - \rho W)^{-1}\varepsilon \quad (\mathbf{6})$$

where ε is i.i.d. and the outcome variable *y* of unit *i* will depend on its own regressors in *X* as well as on the spatial lags of both dependent and exogenous variables of the other units, where these correlations are respectively captured by ρ and θ.As it can be observed, estimation concerns many parameters (the entire set includes ρ ,β ,θ and σ^2) and different frameworks may be considered, with the exception of OLS that would lead to biased estimation of ρ.

The need of a different technique is solved by using the Maximum Likelihood framework, where , since ρ is first estimated through the Concentrated Log-Likelihood function and the estimated $\widehat{\rho}$ is used to obtain $\hat{\delta}$ and $\widehat{\sigma^2}$, that is

[21] At alpha = 0.05

$$\mathrm{Ln\ L}(\rho) = c + \ln|I - \rho W| - \frac{n}{2}\ln S(\rho) \quad \mathbf{(7)}$$

where *c* is the constant term and $S(\rho) = e(\rho)'e(\rho) = e_0'e_0 - 2\rho e_0'e_d + \rho^2 2e_d'e_d$ with $e(\rho) = e_0 - \rho e_d$; $e_0 = y - Z\delta_0$; $e_d = Wy - Z\delta_d$; $\delta_0 = (Z'Z)^{-1}Z'y$; $\delta_d = (Z'Z)^{-1}Z'Wy$. Once estimates are computed, the corresponding Variance-Covariance matrix is $VC(\hat{\rho}, \hat{\delta}) = -H^{-1}$ where H is the Hessian matrix with respect to the two parameters.

Moreover, additional tests are needed to consider the longitudinal property and identify the presence of heterogeneity and spatial autocorrelation in the dataset. The first test will consider the joint presence of spatial autocorrelation and random effects, thanks to the Baltagi, Song and Koh test[22] (Baltagi, Song & Koh, 2003). Under the null hypothesis $\rho = 0 = \sigma_\mu^2$ the statistic

$$LM_j = \frac{NT}{2(T-1)} G^2 + \frac{N^2T}{b} H^2 \sim \chi_k^2 \quad \mathbf{(8)}$$

is Chi-squared distributed under H_0 and $G = \tilde{u}\,(J_T \otimes I_N)\,\tilde{u}\,/\tilde{u}'\,\tilde{u} - 1$, $H = \tilde{u}'(I_T \otimes (W + W')/2)\tilde{u}/\tilde{u}'\tilde{u}$, $b = \mathrm{tr}(W + W')^2/2$, $J_T = \iota_T\,\iota_T'$ where ι_T is a vector of ones and $\tilde{u}$ denotes the OLS residuals. The rejection of H_0 confirms the presence of at least one of the two components and an additional marginal LM tests verifies both cases[23].

Following this result, an Hausman test is then run in order to check whether fixed effects might improve the model (Mutl J. & Pfaffermayr M. ,2011). Under the null hypothesis H_0 standing in favour of random effects, then test statistics

$$H = NT\left(\hat{\theta}_{FGLS} - \hat{\theta}_W\right)'\left(\hat{\Sigma}_W - \hat{\Sigma}_{FGLS}\right)^{-1}\left(\hat{\theta}_{FGLS} - \hat{\theta}_W\right) \sim \chi_k^2 \quad \mathbf{(9)}$$

is Chi-squared distributed. In Equation (**9**), *k* is the number of exogenous regressors , $\hat{\theta}_{FGLS}$ and $\hat{\theta}_W$ are respectively the spatial GLS and within estimators whereas $\hat{\Sigma}_{FGLS}$ and $\hat{\Sigma}_W$ are the corresponding estimates of the coefficients' variance covariance matrices. Once again, the final rejection of H_0 points fixed effects to be the best fit.

[22] The test belongs to the Langrangian Multiplier family.

[23] Where $SLM_1 = \frac{LM_1 - E(LM_1)}{\sqrt{VAR(LM_1)}}$ is the test for the spatial autocorrelation with LM_1 as the square root of the first element in the LM_j formula and $SLM_2 = \frac{LM_2 - E(LM_2)}{\sqrt{VAR(LM_2)}}$ is test for the random effects presence, where LM_2 is the square root of the second element in the LM_j formula.

After testing, the final framework considers a Spatial Durbin Model (including both endogenous and exogenous spatial interactions) together with the estimation of Fixed Effects, which can be written as

$$\widetilde{Shr\_Commt} = (I - \rho W)^{-1}(\tilde{X}\beta + W\tilde{X}\theta) + (I - \rho W)^{-1}\varepsilon \qquad \textbf{(10)}$$

where ε is the random disturbance element of 0 mean and *tilde* indicates the time-demeaned values of our variables following the Fixed Effects framework[24].

Moreover, additional estimates are available in Annex A (i.e. Ordinary Least Squares (OLS) with random and fixed effects as well as Feasible Generalised Least Squares(FGLS) with fixed effects) in order to compare the upcoming results with other panel methods.

[24] In Panel Fixed effects, variables are demeaned by the corresponding time-mean, hence $Shr\_Commt_{i_t} - \overline{Shr\_Commt}_i = \underbrace{(\alpha_i - \bar{\alpha}_i)}_{=0} + (X_{i_t} - \bar{X}_i)\beta + (u_{i_t} - \bar{u}_i)$ where $\overline{Shr\_Commt}_i = \sum_1^T Shr\_Commt_{i_t} \times \frac{1}{T}$, $\bar{\alpha}_i = \sum_1^T \alpha_{i_t} \times \frac{1}{T}$, $\bar{x}_{k,\,i} = \sum_1^T x_{k,i_t} \times \frac{1}{T}$ for each of the *k* regressors in X and $\bar{u}_i = \sum_1^T u_{i_t} \times \frac{1}{T}$ are the *time means.*

5 Findings

5.1 Global and Local Moran's I

An initial description of the spatial pattern characterizing European cross-border commuting outflows is given by Figure 3, where the Global Moran's Is are computed for different years. Following the previous definition of this measure, the commuting propensities of both internal and neighbouring territories are compared to the corresponding sample mean and the position of the outcoming dot on the cartesian plane will return the type of spatial relationship existing between each unit with its closet neighbours.

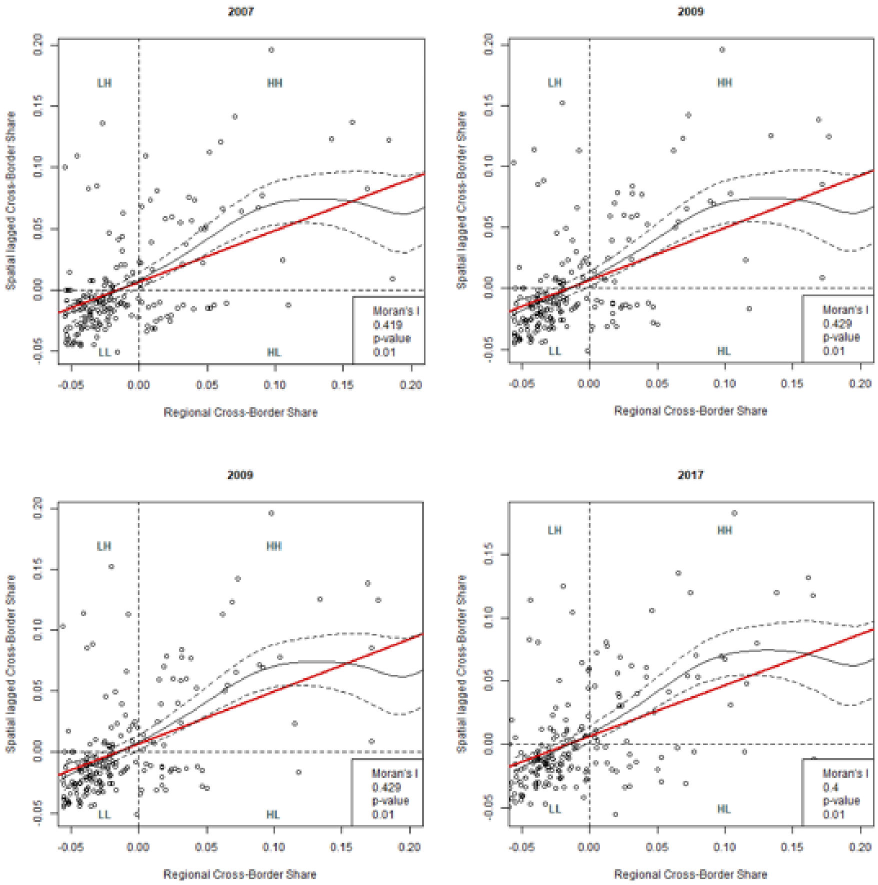


Figure 3- Global Moran's I for different years. Both linear(red line) and non-parametric estimates (continuous black line with dashed 95%C.I) stand in favour of spatial autocorrelation

As it can be noticed in the above Figure 3, each graph can be divided into four areas by two dashed black lines, which denote the average of the sample mean deviations (vertical line) and the corresponding average of the spatial lagged mean deviations (horizontal line), both equal to 0. Starting from the third quadrant, the corresponding spatial cluster includes regions where both internal and neighbouring commuting propensities lie below the sample mean thus representing the "Low-Low" (LL) cluster. Continuing counterclockwise, the "Low-High" (LH) top-left quadrant identifies regions characterized by a low probability to commute and yet surrounded by territories acting differently whereas the top-right “High-High” (HH) quadrant catches those macro-areas where regions share a common and relatively high propensity to commute cross border. Finally, a last “High-Low” (HL) quadrant defines territories of strong internal outbound propensity surrounded by regions showing opposite attitudes. Looking at the graphs, the persistent concentration in the Low-Low cluster together with the positive, constant and significant slope of the spatial linear regression (red line) supports the hypothesis of spatial correlation for EU regions, meaning that there are inter-regional clusters of either Low or High commuting propensity.

Once the general spatial pattern is identified, a second index gives the chance to identify local clusters. Therefore, the Global Moran’s I ratio is reconstructed fixing a unit at the numerator and taking the same calculation with respect to its neighbours (as previously explained in Section 4) thus obtaining the Local Moran’s I with a first quantile cut-off as research design. The outcoming analysis is shown in Figure 4.a and Figure 4.b below for both initial and final years.

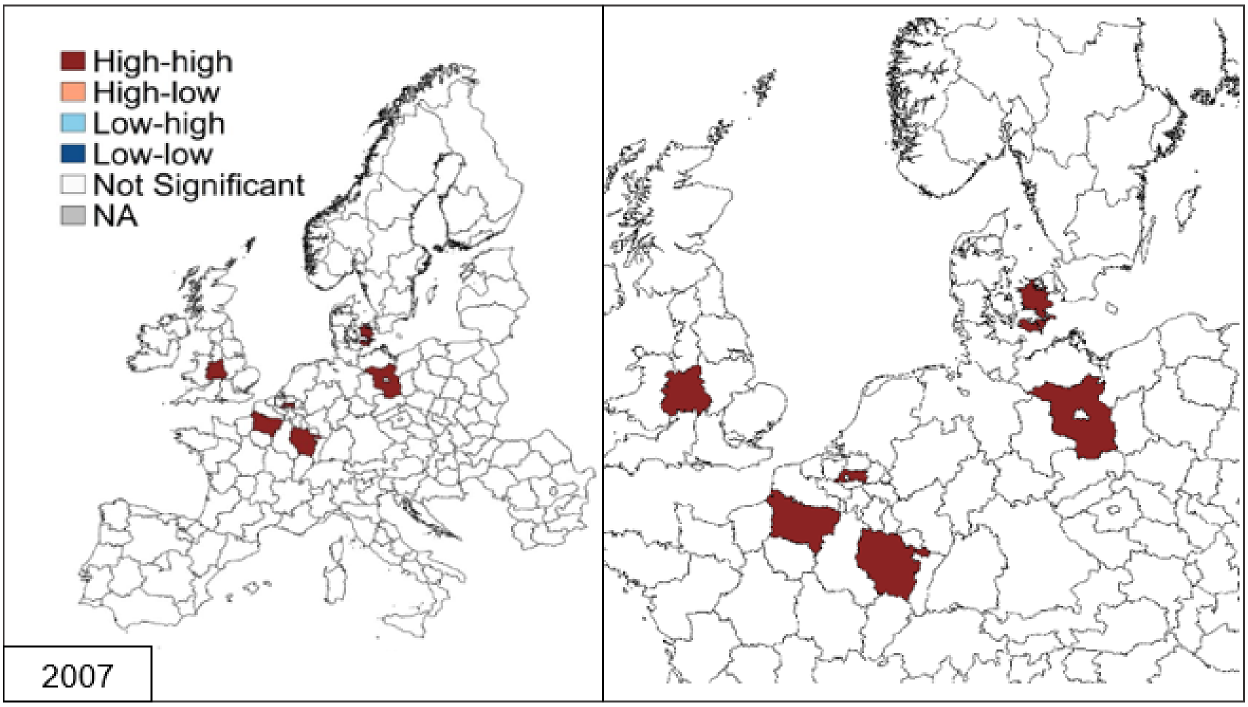
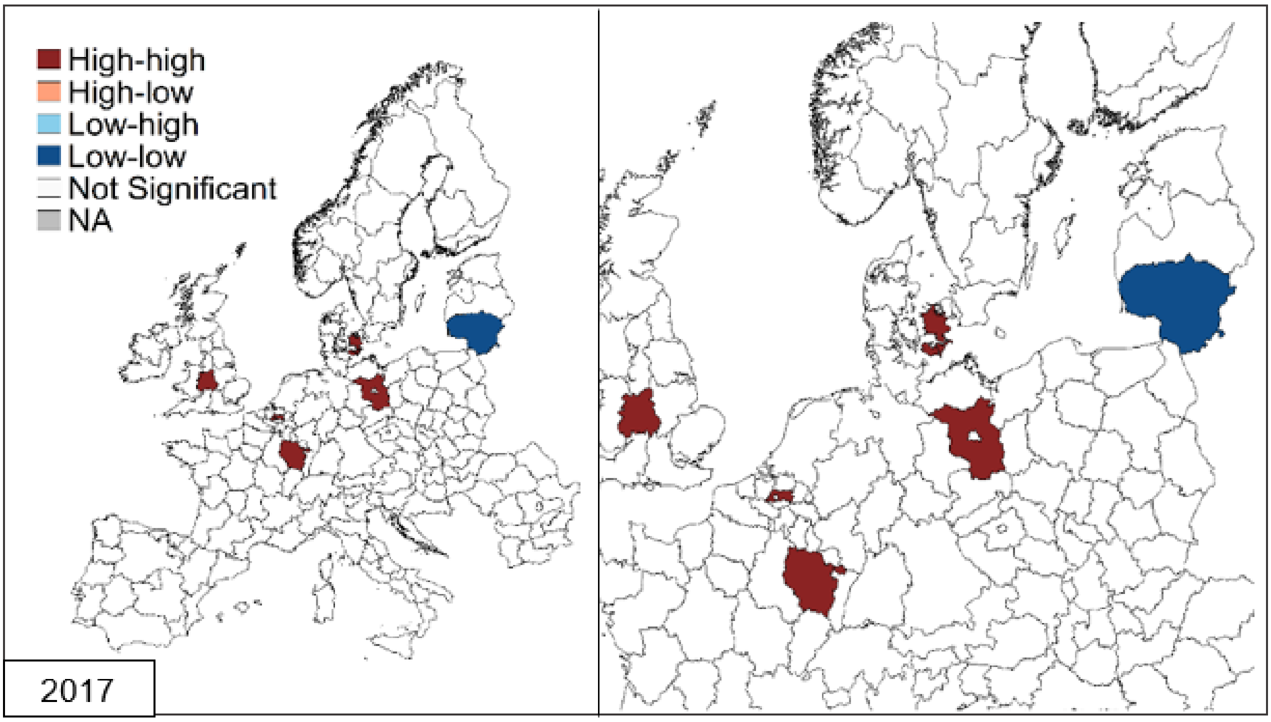


Figure 4.a– Graphical Representation of Local Moran’s I for year 2007 on the entire sample (left) and on significant regions (right). The same results have also been found for year 2009.

Accepting a 10% significance threshold only few clusters can be validly considered. Nevertheless, many interesting insights can still be observed as spatial clusters seem to persist across time. A first remarkable observation regards some of the spotted “hot clusters” and in particular those found for regions close to capital cities, namely the belgian region of Vlaams-Brabant Province (encircling Brussels) or again the german case of Brandeburg (surrounding Berlin) and finally the danish case of Sjælland (next to Copenhagen). These examples provide additional evidence in support to the hypothesis that considers Capital Cities as attractors of external labour force (and especially of high skilled professionals) since workers are appealed by relatively higher wage rates of capital cities as well as by their strong concentration of job opportunities, despite the expensive housing costs that force commuters to live out of city borders (Eurofound, 2016).

Figure 4.b – Graphical Representation of Local Moran's I for year 2017 on the entire sample (left) and on significant regions (right). The same results have also been found for year 2013.



A second consideration interest two territories: the French region of Lorraine and Lithuania (of unique NUTS code) for which borders are shared with foreign territories. Following the existing literature, it emerges that language barriers represent one of the major impediments to commute (K. Bartz & N. Fuchs-Schündeln,2012) since territories with international neighbours experience lower mobility rates compared to those surrounded only by national borders, which seems confirmed in Lithuania but not in the Lorraine, where there is a hot spot. However, a closer look on the foreign neighbours of this region (namely Luxembourg and the Belgian province of Luxembourg) allows to identify some peculiar characteristics. First, the collective participation of these territories to the European Union implies an harmonization of the national legislation systems thanks to the common guidelines that members are forced to apply when enacting laws, as for the employment regulation. Secondly and most importantly, the sharing of the same language (i.e. French) as well as the similarities in their cultural backgrounds support an intense cross-regional inter-dependence among these territories, no matter the country of origin.

5.2 The Spatial Durbin Model

The analysis splits data into three different time intervals, namely the entire Decade (2007-2017) the Recession period (2007 to 2011) and the Post-Crisis Period (2012 to 2017). With respect to the methodology, the final framework includes two out of three potential spatial interactions previously discussed. That is, the dependent variable of each unit is assumed to be correlated not only to its spatial lags (the so-called endogenous effects) but also to the spatial lags of the explanatory variables (or exogenous effects) of its neighbours. The inclusion of these elements has been motivated by some statistical tests however, as shown in Table 1 below, once the exogenous spatial effects are included then the significance of the endogenous autocorrelation vanishes and this supports the idea that the exogenous effects are the main source of spatial inter-dependence, at least in the observed period. Nevertheless, the positive and significant magnitude of ρ (the endogenous spatial autocorrelation coefficient) found in the Decade column seems to confirm the results of the Global Moran's I, which highlights the presence of inter-regional spatial clusters characterized by common commuting behaviours. The last point to clarify before moving to results concerns estimates, here computed according to the Fixed Effect framework, which has been identified as the best fit to data following the Hausman Test in its spatial modeling extension (Mutl & Pfaffermayr, 2011).

Starting from socio-demographics, a first comparison between internal versus neighbouring coefficients focuses on gender and it shows reverse significance during time. Indeed, while the male coefficient is positive and significant (thus confirming MacDonald, 1999; McLafferty & Preston, 1997; Sandow & Westin, 2010) with the only exception for the Regression sub period (which reinforces the idea that the Great Recession has lowered the gender gap in terms of commuting propensities), the spatial lags are statistically different from zero only during Recession time. Again, this may depend on the crisis effects related to the general increase of job uncertainty, which increments workers willingness to accept more distant jobs. This feeling of apprehension, combined to the predominance of males in the sample (i.e. average of 55% males in 2007 and 54% in 2017) has probably exposed male workers to be fired more frequently, thus explaining the positive sign of the resulting coefficient.

Moving to the regional workers age distribution, results seem to confirm previous research (among all, Topel & Ward, 1992) with a decrease of commuting outflows for increasing shares of young workers. This means that elder workers register a relatively higher propensity towards cross-border mobility, which comes from greater household obligations as well as stronger place attachment derived from home ownership, especially when compared to younger individuals (Romani, Surinach, & Artis, 2003; van Ham, Mulder & Hooimeijer, 2001). Moving to the corresponding spatial lags, they do not seem to provide interesting insights.

The hypothesis of innovation as workers' attractor is here reinforced by the results on the economic sectors distribution. That is, using the employment shares of primary, secondary, tertiary and knowledge sectors to proxy the regional work force specialization, then the very same measures can also roughly (and partially) indicate the corresponding regional economic specialization. Looking at the regional coefficient in Table 1, both Decade and Recession periods present significant results at a threshold of 10%, where for higher employment shares in the domestic Knowledge sectors corresponds a decrease in commuting outflows. This result can be interpreted as the ability of origins to be able to retain their own work force the more they are specialised in technological industries. On the other hand, looking at the significant lagged coefficients, than the higher the neighbouring specialization in the Knowledge sector the higher the outflows of the adjacent regions. This result can be interpreted as the greater ability of destinations to attract external workers the more they are specialised in the innovation sector.

Some interesting insights can also be found considering the educational distribution. Looking at the corresponding significant coefficients in Table 1, the results reinforce the belief of a positive schooling effect on commuting at individual (Groot, de Groot and Veneri, 2012) as well as at aggregate level. A second confirm to the previous hypothesis can be observed when looking at the Post-Recession coefficient related to the share of tertiary educated workers of external origin, where the significant negative coefficient gives credit to the existence of a dual-effect concerning skilled workers' outflows, which represents a terrible loss of human capital for the corresponding region of origin as well as a gain of skilled labour force, hence of innovation and competences, for their destinations.

Moving to the regional firm distribution, results support the hypothesis of large business to be a factor that encourages workplace mobility (Scherer,1976) especially when compared to medium and small organizations. Interestingly, opposite effects seem to interest the neighbouring distribution, as the increase of external employment in large companies seems to lower domestic cross-border commuting while minor firms employment registers opposite effects. This supports the idea that given the limited availability of job opportunities, a raise of external employment in jobs that usually imply relatively longer commutes will discourage domestic workers to occupy the same positions, thus lowering domestic cross-border mobility.

Moving to job characteristics, two variables capturing job uncertainty present valid results, namely the regional shares of full-time and of temporary contracts. Specifically, the first positive coefficient extends to the regional aggregation the individual propensity to burden longer commutes for full-time positions (Hong, Lee, Mc Donald,2002; McQuaid,Chen,2011) while the second coefficient reiterates the existing literature that considers temporary employment as a push-factor on workplace mobility (Parenti & Tealdi, 2015) since it entangles workers to their current residence because of the uncertain future of their employment, thus to longer commutes. This condition is particularly amplified by the effects of the economic crisis, as reported in Table 1, that is a period of general and extraordinary high uncertainty.

Following the previous classification in Section 3, the last group left for comments is the one referring to specific regional attributes covering both economical and urban aspects. Starting from the former, the corresponding Unemployment Differential coefficient is significant in the Entire as well as in the Post-Recession period, meaning that regional cross-border mobility increases when the inland unemployment rate is greater than the distance-based weighted average of the other territories, in line with the existing literature (Eliasson et al.,2010;Roberts & Taylor,2017;Crane,1996). The same kind of information is gained with respect to the regional labour income, defined as the Wage Differential, whose significance during the Post-Recession years corroborates the mainstream idea that higher salaries can restrain the native work force to flee away in search for better job opportunities (Reggiani et al.,2011). Interestingly, for both measures, the corresponding spatial lags register a significant impact only when coefficients present the same sign of the domestic case and this supports the spatial correlation hypothesis found in the Global Morans' I.

Moving to the urban attributes, the quality of road infrastructures seems to encourage workers mobility, either referring to the internal or to the external system, as positive and significant results are found for both estimates and confirming the mainstream literature (among all Guirao, Campa et al.,2018). Finally, a last important driver of cross-border commuting is found in the housing costs, where a positive and strong association to longer commutes has been underlined in different studies (Romani et al., 2003, Allen,2014) and it is here corroborated by the corresponding spatial lag, although the modest magnitude of the estimate highlights the inaccuracy of the available proxy, which considers national HPI instead of regional prices.

Table 1- Spatial Durbin Fixed Effect Model Results

	Shr_Commt		
	Decade 07-17	**Recession 07-11**	**Post-Crisis 12-17**
Spatial Autocorrelation			
Dependent Variable: ρ	0.0960.	0.0811	-0.0293
	(0.0510)	(0.0732)	(0.0773)
Exogenous Variables			
Share Male Population	0.0706**	0.0577	0.0561 .
	(0.0242)	(0.0339)	(0.0298)
Job Tenure	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)
Share Full-time Jobs	0.0749***	0.0292	0.0090
	(0.0163)	(0.0222)	(0.0238)
Share Temporary Contracts	0.0084	0.0491**	-0.0230
	(0.0130)	(0.0181)	(0.0178)
Unemployment Rate Differential	0.0038**	0.0020	0.0059*
	(0.0013)	(0.0020)	(0.0027)
Wage Differential	-0.0077	-0.0032	-0.0213.
	(0.0051)	(0.0078)	(0.0119)
Roadquality	0.1877*	0.0393	0.2674*
	(0.0902)	(0.2362)	(0.1065)
Urbanisation Level	-0.0053	0.0007	0.0036
	(0.0215)	(0.0265)	(0.0311)
House Price	0.0000	0.0001	0.0000
	(0.0000)	(0.0001)	(0.0001)

(Continues)

	Shr_Commt		
	Decade 07-17	**Recession 07-11**	**Post-Crisis 12-17**
Age Classes (Ref. Share 50 and Over)			
Share 15-24	-0.0052	-0.1100**	-0.0313
	(0.0292)	(0.0398)	(0.0455)
Share 25-34	-0.0531*	0.0132	-0.1050***
	(0.0212)	(0.0311)	(0.0291)
Share 35-49	-0.0119	-0.0098	-0.0418 .
	(0.0172)	(0.0260)	(0.0237)
Education Level (Ref. Share Primary Education)			
Share Secondary	0.0719***	0.0851***	0.0028
	(0.0149)	(0.0221)	(0.0278)
Share Tertiary	0.0662***	0.0893***	0.0270
	(0.0169)	(0.0245)	(0.0282)
Firms Distribution (Ref. Small Firms)			
Share Medium Size	-0.0161	-0.0301 .	0.0248
	(0.0118)	(0.0157)	(0.0187)
Share Large Size	0.0090	0.0138 .	0.0254*
	(0.0063)	(0.0076)	(0.0123)
Economic Sectors (Ref. Share Primary Sector)			
Share Secondary Sector	-0.0238*	-0.0154	0.0691*
	(0.0120)	(0.0125)	(0.0290)
Share Tertiary Sector	-0.0350*	-0.0092 .	0.0496
	(0.0148)	(0.0166)	(0.0314)
Share Knowledge Sector	-0.0627***	-0.0366*	0.0015
	(0.0148)	(0.0161)	(0.0326)

	Shr_Commt		
	Decade 07-17	**Recession 07-11**	**Post-Crisis 12-17**
(Continues)			
Spatial Lags of Exogenous Variables			
Share Male Population	0.1497	0.2343*	0.0055
	(0.0667)	(0.0932)	(0.0997)
Job Tenure	0.0001	-0.0002	0.0003
	(0.0002)	(0.0002)	(0.0002)
Share Full-time Jobs	-0.0962*	-0.0190	-0.0769
	(0.0423)	(0.0592)	(0.0719)
Share Temporary Contracts	0.0184	-0.0454	0.0213
	(0.0279)	(0.0467)	(0.0352)
Unemployment Rate Differential	0.0056.	-0.0021	-0.0001
	(0.0031)	(0.0052)	(0.0068)
Wage Differential	-0.0057	0.0167	-0.0574 .
	(0.0157)	(0.0213)	(0.0339)
Roadquality	0.6233**	-1.3095	-0.0584
	(0.2131)	(0.8160)	(0.2379)
Urbanisation Level	-0.2103**	-0.0070	-0.3912*
	(0.0810)	(0.0847)	(0.1803)
House Price	0.0001 .	-0.0000	0.0003*
	(0.0001)	(0.0001)	(0.0001)
Age Classes (Ref. Share 50 and Over)			
Share 15-24	-0.0306	-0.1561	-0.1717
	(0.0745)	(0.1199)	(0.1331)
Share 25-34	0.0878 .	0.0131	0.0313
	(0.0451)	(0.0780)	(0.0760)

	Shr_Commt		
	Decade 07-17	**Recession 07-11**	**Post-Crisis 12-17**
Share 35-49	0.0118	-0.0853	0.0193
	(0.0347)	(0.0695)	(0.0577)
Education Level (Ref. Share Primary Education)			
Share Secondary	-0.0529 .	-0.0481	-0.0969 .
	(0.0286)	(0.0492)	(0.0588)
Share Tertiary	-0.0038	-0.0652	-0.1455*
	(0.0386)	(0.0675)	(0.0662)
Economic Sectors (Ref. Share Primary Sector)			
Share Secondary Sector	0.0459 .	-0.0097	0.0929
	(0.0256)	(0.0298)	(0.0873)
Share Tertiary Sector	0.0434	0.0718	0.0432
	(0.0293)	(0.0375)	(0.0916)
Share Knowledge Sector	0.1140***	0.1421***	0.1500
	(0.0341)	(0.0427)	(0.1003)
Firms Distribution (Ref. Small Firms)			
Share Medium Size	0.0597*	0.0079	0.0060
	(0.0277)	(0.0417)	(0.0537)
Share Large Size	-0.0376**	0.0030	-0.0646*
	(0.0141)	(0.0197)	(0.0312)
LogLik	7117.975	3499.66	3515.18
Num. obs.	2145	975	1170

***p < 0.001, **p < 0.01, *p < 0.05, . p < 0.10

6. Conclusions and Policy Implications

Commuting shapes countless everyday-lives around the world, with dynamics varying from city to regional and cross regional levels. In Europe, the creation of a common legislation system - through the implementation of several international agreements such as the European Economic Community and the Schengen Agreement – implies freedom of movement for workers living in any EU member state to search for job opportunities without any geographical restriction or discrimination deriving from their nationality.

Taking Norway, Switzerland and the EU-28 members as reference, the analysis consider the inter-regional commuting behaviour of 195 territories over the decade 2007-2017 thus including the impacts of the 2008 Recession. Thanks to the longitudinal property of the dataset, the adoption of the Fixed Effect framework allows to capture cross-border commuting driving factors considering any time variation and heterogeneity of the sample, where data are manipulated in order to eliminate time influence on variables as well as any regional idiosyncrasy (i.e. cultural, institutional etc.) that characterizes a particular territory. Then, the tested presence of spatial interactions redefines the previous framework with the inclusion of neighbouring effects on regional workplace mobility through a Spatial Durbin Model.

The outcoming analysis aims to explore not only the potential drivers of regional commuting outbounds, that literature mainly links to socio-demographic, occupational and economic features, but also to examine whether significant individual effects maintain their magnitudes when data are aggregated at regional level and how the spatial context affects regional behaviours.

With respect to socio-demographic characteristics, individual studies identify middle-aged (namely 50 years old and over) highly educated male workers as more keen to commute and aggregation seems to confirm the individual results (Sandow & Westin, 2010; Booth, Francesconi & Garcia-Serrano, 1999; McQuaid & Chen, 2011). Under the advisory perspective, profiling the mostly hit categories can help to better understand the phenomenon however, policymakers should carefully consider these information when planning their guidelines since any action targeted at reducing the length of the commute for a particular group could disadvantage workers who are not targeted (Ma & Banister, 2006; Martin, 2001). Nonetheless, the differences highlighted by socio-demographic breakdowns can help to search for the origins of these variations as in the case of gender, where unbalanced household responsibilities and gender pay-gaps play a crucial role in shaping different commuting propensities for men and women, because of the unequal job opportunities (Turner & Niemeier, 1997; Madden, 1981; Waldfogel, 2007).

Moving to occupational characteristics, interesting results find identical dynamics at individual as well as at regional level for variables related to job security, namely the duration and the temporality of the current occupation (van Ham et al., 2001; Parenti & Tealdi,2015). Here, significant coefficients support the literature that considers job stability as an important driver of commuting where the increase in the average of the regional job tenure attract inland as well as foreign workers while the more consistent usage of temporary contracts encourage cross-border outflows, especially during an economic recession. Moreover, the significance of the corresponding coefficient in the sole Recession period supports the hypothesis that temporary contracts might be useful in preserving jobs during crisis, offering a flexible tool for employment adjustments (Birgit & Kraemer,2010). In light of these results, the difficulties related to the research of sustainable solutions balancing employment protection with labour market flexibility should not deflect the attention of national and regional governments from the risks of an unregulated usage of temporary contracts in terms of resilience to negative shocks, especially when regular employment is protected by strict rules that encourages temporary employment and slows job creation during recovery (Hijzen, Kappeler et al.,2017).

Literature also highlights an individual propensity towards mobility for those employed in post-industrial activities (van Ham et al., 2001), namely Tertiary and Knowledge sectors, although different dynamics seem to occur at regional level. That is, the Knowledge sector appears to be an important attracting factor of external workers as well as a relatively effective retaining factor of the domestic labour force. The intense employment of R&D activities, which characterizes this sector, gives credit to the hypothesis of Innovation as positive spillover for the entire economic system thanks to the development of new technologies that ameliorates products, services and their sustainability. Therefore, policymakers should not underestimate the potentiality of knowledge capital as contributor of economic growth and promote private-public sectors' partnerships as well as keep affordable patenting costs and efficient procedure times in order to make ideas quickly available on the market and improve the competitiveness of regional enterprises and institutions.

In support of the previous hypothesis, results on the regional educational distribution identify workplace mobility to be positively affected by increasing shares of highly educated workers (hence endorsing individual effects resulting in McQuaid & Chen, 2011 and Groot, de Groot & Veneri, 2012) as well as negatively influenced by the corresponding spatial lags, especially with respect to tertiary educated. This mechanism could either depend on a positive externality deriving from a higher specialization of the neighbouring labour force or, more reasonably, on the increasing availability of highly educated workers that are usually willing to move for rewarding job conditions (van Ham & Hooimeijer, 2009). Following this second interpretation, it is easy to reckon the terrible loss of human capital for those territories unable to offer good job opportunities to their skilled working class but also the incredible opportunity for external territories to gain skilled workers without any need of investment in their education or training (a phenomenon commonly known as “Brain-Drain-and-Gain”, Cavallini et al., 2018).

Finally, a last group of regional characteristics tests for the significance of different aspects. Starting from the economic system, two indexes summarizing the wage attractivity as well as the unemployment situation with respect to the surrounding territories are included and the sporadic significance of the outcoming coefficients corroborates the existing literature (Parenti & Tealdi, 2015;Van Ommeren & Dargay, 2006) and highlights the need to consider more accurate proxies, a limit that recurs also for the measurements on urbanization and on house prices.

Moving to geographical characteristics, the importance of urbanization is underlined first by the descriptive summaries on Capital Cities both in Section 1 and Section 5 as well as by the strong significance of the road quality index in the regression analysis, where the positive signs of both internal and external coefficients emphasize the importance of transportation infrastructures to enhance territories interconnections.

Today, urban developers are asked to organize territories in efficient networks without ignoring the increasing importance that concepts like livability and sustainability have now in the public debate. Hence, the traditional industrialization process that aims to reach peripheral areas, has now been replaced by a new tendency that promotes urban-rural synergies in order to preserve local economies from the population decline of rural areas (Cabus & Vanhanerberke, 2003). The mutual benefits of such interdependence combine the better life quality of the countryside to the innovation and creativity of urban areas (Partridge, Ali & Olfert, 2010) thanks to the development of solid transportation and communication systems, which are crucial for the success of these synergies.

In lights of these results, the future work agenda aims to explore both limits and potentialities of this explanatory study. Starting from the dataset, information on distance and time duration of commutes might give a more accurate measure of the phenomenon as well as the research of better proxies for several explanatory variables can improve the validity of the analysis. In addition, the huge heterogeneity of European territories expressed through their geographical, economic and cultural variety highlights the need to focus on a lower level of aggregation that might consider provinces rather than regions in order to tailor a more realistic picture of the occurring dynamics.

Finally, the variety of perspectives under which commuting can be studied (as confirmed by the centrality of the spatial context) underlines the importance to consider different approaches at once. Following this idea, the future research will examine the potentiality of the network analysis to study cross-border relationships and focus on the intensity of commuting flows.

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Annex A

Table A- Alternative Panel Models: OLS random effects, OLS Fixed Effects and FGLS fixed effects to account for heteroskedasticity and autocorrelation in the error terms

Shr_Commt

	07-17			07-11			12-17		
	(1) RE_OLS	(2) FE_OLS	(3) FE_FGLS	(1) RE_OLS	(2) FE_OLS	(3) FE_FGLS	(1) RE_OLS	(2) FE_OLS	(3) FE_FGLS
Share Male Population	0.1011***	0.0878**	0.0948***	0.0954*	0.0796*	0.0606	0.1076**	0.0863*	0.0973**
	(0.0264)	(0.0274)	(0.0229)	(0.0385)	(0.0401)	(0.0386)	(0.0349)	(0.0357)	(0.0322)
Job Tenure	-0.0002**	-0.0002**	-0.0002**	-0.0001	-0.0002 .	-0.0002 .	-0.0002 .	-0.0002*	-0.0002 .
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share Full-Time Jobs	0.0272	0.0590**	0.0306 .	-0.0208	0.0182	0.0166	-0.0601*	0.0066	0.0203
	(0.0182)	(0.0188)	(0.0169)	(0.0266)	(0.0278)	(0.0269)	(0.0270)	(0.0296)	(0.0271)
Share Cohabitating Partners	0.0096	0.0096	0.0046	-0.0562**	-0.0339	-0.0264	0.0537*	0.0283	0.0395 .
	(0.0104)	(0.0106)	(0.0104)	(0.0204)	(0.0208)	(0.0203)	(0.0220)	(0.0221)	(0.0205)
Share In-House Offspring	-0.0096	-0.0050	-0.0129	0.0185	0.0140	0.0038	-0.0386	-0.0438 .	-0.0544*
	(0.0155)	(0.0153)	(0.0131)	(0.0208)	(0.0201)	(0.0196)	(0.0240)	(0.0234)	(0.0219)
Share Temporary Contracts	0.0022	0.0205	0.0138	-0.0031	0.0385 .	0.0478*	-0.0512*	-0.0253	-0.0160
	(0.0137)	(0.0142)	(0.0140)	(0.0199)	(0.0209)	(0.0205)	(0.0215)	(0.0236)	(0.0223)
Unemployment Rate Differential	0.0007	0.0014	0.0013	-0.0018	-0.0005	-0.0000	-0.0058*	-0.0035	-0.0002
	(0.0013)	(0.0013)	(0.0014)	(0.0021)	(0.0020)	(0.0020)	(0.0027)	(0.0027)	(0.0027)
Wage Differential	-0.0054	0.0001	-0.0035	-0.0126*	-0.0043	-0.0036	-0.0152*	0.0011	-0.0011
	(0.0044)	(0.0059)	(0.0071)	(0.0057)	(0.0107)	(0.0105)	(0.0061)	(0.0128)	(0.0137)
Roadquality	0.3608***	0.2633**	0.2416**	0.4920**	-0.1342	-0.0576	0.3493***	0.2700*	0.2615*
	(0.0797)	(0.0880)	(0.0880)	(0.1501)	(0.2863)	(0.2983)	(0.0917)	(0.1049)	(0.1057)
Urbanisation Level	0.0085	0.0181	0.0113	-0.0069	0.0063	0.0013	0.0151	0.0209	0.0215
	(0.0257)	(0.0288)	(0.0299)	(0.0375)	(0.0508)	(0.0518)	(0.0317)	(0.0371)	(0.0378)

Annex A

Table A- Alternative Panel Models: OLS random effects, OLS Fixed Effects and FGLS fixed effects to account for heteroskedasticity and autocorrelation in the error terms

Shr_Commt

	07-17 (1) RE_OLS	07-17 (2) FE_OLS	07-17 (3) FE_FGLS	07-11 (1) RE_OLS	07-11 (2) FE_OLS	07-11 (3) FE_FGLS	12-17 (1) RE_OLS	12-17 (2) FE_OLS	12-17 (3) FE_FGLS
(Continues)									
Age classes (Ref. Share 50 and over)									
Share 15-24	-0.0481	-0.0853**	-0.1158***	-0.0800 .	-0.1353**	-0.1679***	-0.0369	-0.1071*	-0.0952 .
	(0.0294)	(0.0298)	(0.0293)	(0.0421)	(0.0427)	(0.0425)	(0.0516)	(0.0527)	(0.0490)
Share 25-34	-0.0690***	-0.0865***	-0.0884***	0.0207	0.0038	0.0072	-0.1016***	-0.1362***	-0.1324***
	(0.0199)	(0.0202)	(0.0197)	(0.0352)	(0.0363)	(0.0365)	(0.0291)	(0.0299)	(0.0283)
Share 35-49	-0.0396**	-0.0493**	-0.0676***	-0.0294	-0.0477	-0.0592 .	-0.0482*	-0.0639**	-0.0771***
	(0.0153)	(0.0153)	(0.0159)	(0.0292)	(0.0296)	(0.0304)	(0.0226)	(0.0229)	(0.0223)
Education Level (Ref. Share Primary Education)									
Share Secondary	0.0417**	0.0500***	0.0429*	0.0591**	0.0831**	0.0763**	-0.0172	-0.0309	-0.0376
	(0.0139)	(0.0144)	(0.0167)	(0.0226)	(0.0253)	(0.0258)	(0.0262)	(0.0283)	(0.0279)
Share Tertiary	0.0631***	0.0633***	0.0371*	0.0950***	0.0901**	0.0668*	0.0131	-0.0102	-0.0155
	(0.0165)	(0.0171)	(0.0177)	(0.0267)	(0.0292)	(0.0286)	(0.0271)	(0.0287)	(0.0281)
Firms Distribution (Ref. Small Firms)									
Share Medium Size	-0.0222	-0.0230	-0.0091	-0.0454 .	-0.0451 .	-0.0281	-0.0048	-0.0081	-0.0048
	(0.0141)	(0.0140)	(0.0121)	(0.0238)	(0.0233)	(0.0223)	(0.0211)	(0.0208)	(0.0172)
Share Large Size	0.0073	0.0053	0.0130*	0.0202*	0.0148	0.0175 .	0.0189	0.0055	0.0012
	(0.0072)	(0.0071)	(0.0066)	(0.0097)	(0.0094)	(0.0093)	(0.0135)	(0.0135)	(0.0119)
Economic Sectors (Ref. Share Primary Sector)									
Share Secondary Sector	-0.0066	-0.0042	-0.0039	-0.0126	-0.0101	-0.0095	0.1050***	0.0914**	0.0809**

Annex A

Table A- Alternative Panel Models: OLS random effects, OLS Fixed Effects and FGLS fixed effects to account for heteroskedasticity and autocorrelation in the error terms

Shr_Commt

	07-17			07-11			12-17		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	RE_OLS	**FE_OLS**	**FE_FGLS**	**RE_OLS**	**FE_OLS**	**FE_FGLS**	**RE_OLS**	**FE_OLS**	**FE_FGLS**
	(0.0112)	(0.0111)	(0.0095)	(0.0132)	(0.0130)	(0.0126)	(0.0296)	(0.0310)	(0.0301)
Share Tertiary Sector	-0.0224 .	-0.0344**	-0.0092	-0.0071	-0.0182	-0.0151	0.0851**	0.0584 .	0.0579 .
	(0.0131)	(0.0133)	(0.0112)	(0.0168)	(0.0169)	(0.0163)	(0.0302)	(0.0331)	(0.0315)
Share Knowledge Sector	-0.0163	-0.0297	-0.0075	-0.0038	-0.0069	-0.0047	0.0646 .	0.0074	0.0171
	(0.0158)	(0.0159)	(0.0132)	(0.0190)	(0.0190)	(0.0182)	(0.0341)	(0.0368)	(0.0348)
Geographical Dummies:									
CAPITAL	-0.0415 .			-0.0523*			-0.0393 .		
	(0.0222)			(0.0233)			(0.0229)		
EXT	-0.0192*			-0.0187*			-0.0147		
	(0.0092)			(0.0093)			(0.0095)		
BORDER	-0.0392 .			-0.0349			-0.0417 .		
	(0.0212)			(0.0213)			(0.0217)		
INTERNAL	0.0281*			0.0226			0.0387		
	(0.0133)			(0.0137)			(0.0132)		
R^2	0.0674	0.0718	0.9833	0.0949	0.0830	0.9900	0.0929	0.0811	0.9882
Num. obs.	1856	1856	1856	845	845	845	1011	1011	1011

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, . $p<0.10$

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