Essays in Applied Economics

Chiara Baggetta

Department of Economics
University of Genoa

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Supervisors:
Prof.ssa Anna Bottasso
Prof. Maurizio Conti

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Ad Andrea, per sempre con noi

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work, joint with others as specified in the text. In particular, in the third chapter (co-authored with Marta Santagata and Gianluca Cerruti) my main contribution consists of reviewing the literature, the text analysis to build the database of street names, and writing conclusions. Authors contributed equally to the other parts of the chapter.

Chiara Baggetta

Preface

This work includes the results of a broad research carried out during the PhD course in Economics and Political Economy at the University of Genoa.

The first part of this thesis consists of two studies that can be ascribed to the literature on the rural and urban divide.
In particular, the First Chapter is devoted to build a new indicator able to capture the EU-28 territorial heterogeneity. Following Pagliacci (2016), the Fuzzy Rurality Indicator (FRI) is a multidimensional index that defines a more appropriate way to describe the rural-urban continuum, taking into account three thematic approaches: sector-based, demographic and territorial. The results show a clear turnaround, especially with respect to the Eurostat classification, highlighting a prevalent rural continent. The main contributions of the chapter to the literature are the new taxonomy that defines rural and urban areas and the discovery that Europe is prevalently a rural continent. This shortcoming is crucial as identifying territorial differences has important policy implications.

The identification of territorial characteristics is a key element also for the Second Chapter of the thesis. This contribution is written during my visiting period at the European Commission Joint Research Centre and deals with the ex-post evaluation of the Common Agricultural Policy in the period 2011-2015. The Common Agricultural Policy (CAP) is one of the most ancient European Union (EU) policies which has evolved overtime. Traditionally, the CAP supports farmers' activities and maintains fair prices for agricultural producers and consumers; more recently, its objectives include promoting a balanced territorial development in order to reduce the rural-urban divide across and within Member States. Therefore, the CAP has turned into a policy characterised by many instruments which allow all the actors involved (farmers, MS, consumers, etc…) to adopt different implementation choices. The current study considers the CAP as a multivalued discrete treatment and infers impact causality through the Generalized Propensity Score (GPS), approach developed by Imbens (2000). Beyond the baseline treatment (Low CAP), the other CAP policy mixes are based on the access to three main types of CAP funds (Direct Payments, Market

Measures and Rural Development). The analysis refers to the period 2011-2015 for the EU-28 NUTS3 regions and focuses on three outcomes (GDP per capita, Gross Value Added in Agriculture and Employment in Agriculture). Main results show that Direct Payments positively affect GDP per capita, while Market Measures and Rural Development mainly foster agricultural employment and agricultural productivity. Furthermore, another contribution of this work regards the concept of convergence between rural and urban regions which are defined in the new and innovative way that is described in the first chapter of this thesis.

The second part of this work consists of a study[1] that belong to the literature on the process of place naming in relation to political and cultural changes.

Streets names reflect the commemorative decisions of a community since they represent not only the historical and political causes of naming and renaming process that a city experiences, but also social and cultural values. Since history is written by winners, minorities are usually underrepresented in commemorative streets names. Women surely do not constitute a minority, but they are historically excluded from the public sphere and, consequently, they do not frequently appear in street names.

This study, exploiting street names as source of geographical and cultural data, aims to analyse individual perception towards gender equality through urban toponymy in Italian municipalities. Specifically, different specifications of a Probit model are estimated to observe how a change in the ratio of streets named after women is related to the probability of an individual to have a more equitable gender perception.

Results show that, even when controlling for a complete set of geographic, socio economic and historical controls, in the Italian municipalities with a higher percentage of streets named after female, there is more awareness about gender bias and a greater attitude towards gender equality, even if still far from parity.

[1] Co-authored with Marta Santagata and Gianluca Cerruti

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CHAPTER 1
How rural is the EU-28? A new taxonomy for the European Union

Abstract

This paper provides a multidimensional and continuous indicator of rurality by applying fuzzy logic. The aim of this new indicator is capturing the EU-28 heterogeneity. Fuzzy Rurality Indicator (FRI) consists in a step forward with respect to existing definitions in finding an appropriate way to describe rural-urban continuum. The analysis takes into account 1062 regions at NUTS3 level of aggregation. It considers three thematic areas: agriculture, demography and landscape. The results are quite surprising and show a clear turnaround, especially in comparison to Eurostat classification. First, EU-28 seems prevalently a rural territory when FRI is considered in terms of land area and population. Secondly, FRI proposes a different composition of rural and urban categories with respect to the existing taxonomies. The paper stresses the fact that a new definition of rurality is urgent because identifying geographical differences has relevant policy implications and requires further socio-economic analysis. Maybe, the time is ripe for asking European institutions a new way to define rurality.

1. Introduction

This paper aims to build a new measure of rurality based on a multidimensional and continuous indicator providing a better understanding of the rural-urban continuum that characterizes the EU-28.

The concept of rurality is vague and convergence over its definition still lacks. Defining which territorial units are rural and which ones are urban is a critical task and has changed overtime. Since the end of the Second World War, most studies refer to a clear division between cities and countryside. Researchers define “rural” as “not urban” and vice versa (Sotte et al., 2012). However, society has changed and the need for a better definition of rurality for policy and practice become more and more relevant. Therefore, rurality has continually evolved in its conceptualization (Nelson et al., 2021). Since 1950s, cities represent traditionally the heart of post-war economic engine (de Beer et al., 2014), while rural areas are considered less developed zones which suffer from several socio-economic issues such as declining agricultural activities, depopulation due to migration towards urban centres and poor economic development and social dynamism (Pagliacci, 2016). From the economic theory point of view, rural areas are considered underdeveloped and economically marginalized. Some theories try to explain relevant macroeconomic phenomena by studying relationships between more developed and peripheral zones. Examples of this trend can be found in circular cumulative causation theory (Kaldor 1970), in coreperiphery models (Friedman 1972) and in new economic geography theory (Krugman 1991a, 1991b). Therefore, European Union can just design policies at supporting rural areas in order to foster territorial cohesion. Nevertheless, since the 1970s, a clear distinction between urban and rural areas appears no longer feasible because cities and their rural hinterlands become deeply knitted (Bengs & Schmidt-Thomé, 2005; Gulinck & dewaelheyns, 2008; Haase & Totzer, 2012; de Beer et al., 2014). On the one hand, the strengthening of small and medium firms has fostered and contributed to the economic renaissance of rural areas (Courtney et al., 2007,2008; Priore & Sabel, 1984; Brusco, 1989; Becattini, 1998). On the other hand, improvement in infrastructure (Agarwal et al., 2009) and ICT diffusion (Castells, 1996) have helped to reduce the rural-urban divide, promoting tourism and recreation activities in rural areas (Hoggart et al., 1995; Paniagua, 2012).

Overtime, regional imbalances have increased across EU and have reshaped rural-urban relationships (European Commission, 2010). Furthermore, EU Eastern enlargements have contributed to the abovementioned direction. Therefore, existing territorial complexity has to be translated in updated definitions of rurality. For instance, as Cloke (1977) suggests, a new rural-urban definition that highlights the continuum between urban areas and remote rural regions is needed. This issue is very relevant from policy-implications point of view: identifying and selecting properly regional typologies will allow better addressing alternative policies (and funds allocation). In the same direction, Romagnoli (2002) proposes a transformation of the traditional city-countryside duality into a continuum based on land use, spanning from high intensity (city-dormitory) to low intensity (nature reserves). Within this spectrum, various ideal categories can be identified, each corresponding to different stages of the development process.

Nevertheless, as Pagliacci (2016) notices, characterizing rural-urban continuum is not an easy task. Even if some steps forward in converging to homogenous meaning have been taken in the 1990s, a univocal definition of rurality still lacks at international level. For the time being, the most frequent definitions adopted in analysis are those by OEDC (1994, 1996a, 1996b, 2006) and by European Commission (Eurostat, 2010). However, Camaioni et al. (2013) highlight that the abovementioned definitions measure rurality too roughly, neglecting the nuanced EU rural-urban situation.

Pagliacci (2016) tries to move forward and to quantify the concept of rural-urban continuum. Adopting a multidimensional approach, the author creates a comprehensive and continuous indicator of rurality: the Fuzzy Rurality Indicator (FRI). This indicator is built by means of fuzzy logic (FL). Being both continuous and multidimensional, FRI provides a step forward in defining rural-urban typologies throughout EU 28 at NUTS3 level.

The aim of this paper is to enrich the field of rurality indicators. Therefore, the author tries to move forward computing a fuzzy logic with updated data to present a new rural-urban classification for EU-28 Member States. Since in 2020 the 35% of EU total expenditure is allocated to Common Agricultural Policy (CAP), it is worthy to investigate whether European Union is correctly identifying and differentiating rural and urban areas. Maybe the time is ripe to ask European institution to explore new methodologies to classify EU territories. The novel contribution of this study consists in updated data referring to 2018 which overturn the previous studies. Results highlight a very rural continent, which is not correctly represented by the most common taxonomy adopted in the majority of the studies that is the Eurostat one.

The paper is organized as follows. The second section provides the concept of rurality's literature review which briefly illustrates alternative approaches in distinguishing rural from urban territorial units overtime. Then, in section 3, data and descriptive statistics are reported. Section 4 describes in detail the fuzzy logic methodology and how it is applied to the case under study. The fifith section shows the main results and the robustness check at both EU and national level and their policy implications. Finally, the last section concludes.

2. Related literature

Van der Ploeg et al. (2000) theorize the concept of rurality and, broadly speaking, of rural development as a “disputed notion, both in practice, policy and theory”. Still nowadays, the lack of a shared theoretical definition of what is rural persists in literature and this influences the originated taxonomies.

Defining and measuring rurality is a crucial topic and has many implications for policy makers from different points of view. For instance, in education, the main issue tied to rural communities is schooling access, financial support and school attendance (Crouch and Nguyen, 2020; Sher, 2019; Beeson and Strange, 2003). Maltzan (2006) shows that students who live in rural areas are less likely to attend a postsecondary school and even to conclude their education path with a degree. Regarding economic development, the main problems are associated with labour market conditions, financial subsidies and income (Ellis and Biggs, 2001; Galluzzo, 2018). From a healthcare system standpoint, research interests focus on well-being in rural areas, access to facilities and insurance coverage (Mao et al., 2015; Zhao et al, 2019). As regards environmental sustainability, rurality is linked to issues like land and water exploitation (Brown et al., 2005; Chen et al., 2018). A frequent mistake in literature concerning rurality is considering rural areas homogenous and subject to the same conditions (National Academies of Sciences, Engineering and Medicine, 2016). Actually, also within country, rural zones are very heterogeneous. In fact, rural areas closer to cities are usually more developed and have different needs in comparison to those that are in a more remote position (Montezuma et al. 2021).

Nowadays, rural areas’ challenges and shortcomings are several. For this reason, building a measure of rurality that gathers multiple aspects becomes essential. In literature, it is possible to point out both qualitative and quantitative definitions of rurality. The former focuses on people’s social-cultural dimensions, their habits and perceptions (Woods, 2009). While the latter approach is considered more reliable by researchers and policy makers since they can construct measures that include multiple dimensions that characterize rurality. It is largely widespread that there is no convergence to a universally shared measure for describing rurality in all circumstances and for all purposes (Doogan et al., 2018). Given the variety of quantitative rurality definitions, it is important to briefly describe the most common components of rurality, units of measurements and most consistently methods adopted to identify suitable measures of rurality (Nelson et al., 2021).

The concept of rurality has evolved overtime due to technological changes and an increasing urbanization. In fact, worldwide rural population has steadily declined resulting by migration to urban areas due to limited job opportunities. In the last 70 years, global urban population has increased approximately by 3.5 billion (UN DESA, 2018). The projections show that the urban population is expected to rise by another 13%, increasing from 55% to 68%. Consequently, these data suggest that the concept of rurality has changed a lot and will change again in the future.

In order to understand how the concept of rurality has evolved overtime (Cloke, 1986; Timmer, 1988; Basile and Cecchi, 1997), it could be useful to show a brief overview going through decades. In a recent study, Sotte et. al (2012) focus on Italy as a case study and distinguish three stages of rurality: an agrarian rurality model, an industrial rurality model and a post-industrial rurality model. Authors have tried to combine agricultural economists and regional economists' perspectives. In the 1950s and 1960s, rurality is interpreted as "not-urban". The *agrarian rurality model* is characterized by a sector-based approach: agricultural employment is often taken as a proxy for rurality. At that time, rural areas are perceived as underdeveloped regions whose only aim is to supply urban areas with food and low-cost labour force. In this period, the Common Agricultural Policy (CAP) is introduced and its primary aim is to ensure EU food security, to support agricultural products price and to stabilise food market (Lenschow, 1999).

Between the 70s and the 90s, the *industrial rurality model* has progressively substituted the agrarian rurality model. In this framework, agricultural activities start to decline and rural depopulation becomes an increasing trend. In this context, rurality is defined according to demographic criteria (e.g., population density). In fact, indicators of rurality such as the one by OECD (which is still utilised and worldwide accepted) appears for the first time. At the same time, some rural areas experience great development paths due to economic dynamism, social mobility and territorial cohesion (Esposti and Sotte, 2002). In this context, many small and medium size enterprises boost industrial development. However, agricultural sector remains a reserve for labour force and capital for the secondary sector.

In the 90s, new priorities of EU political agenda pay more attention to food security and quality. Therefore, a new concept of rurality emerges, the so-called *post-industrial rurality model*. In this framework, two new elements characterise rural areas: territorial dimension and heterogeneity. Rural areas gain a new role in terms of integration between rural and urban territories and the sector-based approach slowly disappears. Rural regions supply the society with a wide set of services tied to public goods, environmental goods such as biodiversity and clean water and air; and cultural goods such as historical heritage and food traditions. The second change regards different forms of rural-rural and rural-urban diversity. This polymorphism of rural space within the post-industrial rurality model points out the need of a rurality definition able to capture its multidimensionality (Sotte et al., 2012).

In the 80s and 90s, Nelson et al. (2021) note that rurality research further develops adopting modern spatial analysis and statistical techniques such as modern Geographic Information Systems (GIS) (Cromartie and Swanson, 1996; Mitchell and Doyle, 1996).

In the 2000s, the focus of analysis is on regional measures of rurality. For instance, Ocana-Riola and Sanchez-Cantalejo (2005) propose a specific municipality-based measure of rurality for Spain, while Bogdanov et al. (2008) use more than forty factors grouped into eight principal components to define rurality in Serbia.

In the 2010s, research on rurality is mainly policy-oriented. For instance, Li et al. (2015) creates an index to measure the degree of rurality at county level in China and to evaluate the correlation between rurality and socio-economic and geographical indicators.

Overtime, the concept of rurality has evolved from the basic dichotomy of otherness (*not-urban*), assuming a more transversal connotation as well-explained in Rocchi and Turchetti (2013). In fact, the authors highlight how the many interactions between urban and rural contexts imbue the concept of rurality which takes on a cross-sectoral significance, establishing a strong connection to the area's resources and socio-economic development. Consequently, this new conceptualisation of rural construct implies the need for more complex measures that include multiple factors and sophisticated techniques (Nelson et al., 2021).

Since society has continuously changed and defining properly rurality for policy purposes becomes more and more urgent, the conceptualization of rurality is a fluid concept. The most common components used in creating quantitative rurality measures are demographic indicators such as population density and size, age, percentages about religious or different ethnics presence (Cloke, 1977; Li et al., 2015; Romano et al., 2016; Zhao et al., 2019; Gajic et al., 2018; Mao et al., 2018). For instance, Cloke (1977) creates a measure of rurality that includes demographics, migration, commuting patterns, population density and distance to urban centres (Nelson et al., 2021). Furthermore, many studies use rurality measures within healthcare field in terms of urban-rural population relating to healthcare services (Riddick and Leadley, 1978).

Remoteness to metropolitan areas and accessibility (e.g., access to railroads and ports) are other relevant indicators that contribute to define a territory as rural (Cromartie and Swanson, 1996; Caschill et al., 2015; Doogan et al., 2018; Madu, 2010; Nong, 2015). Surely, several measures of agricultural production and land use are unavoidable elements that mark rural areas (e.g., percent of agriculture, percent of land cover) (Blunden et al., 1998; Bogdanov et al., 2008; Peng et al., 2016; Hoffman et al., 2017; Terashima et al., 2014; Prieto-Lara and Ocana-Riola, 2010). Furthermore, economic measures are usually part of rurality indicators in terms of unemployment rate, income, educational level, poverty rate, health professionals, non-agricultural jobs (Smith and Parvin, 1973; Blunden et al., 1998; Bogdanov et al., 2008; Beyon et al., 2016; Mao et al., 2015; Hedlund et al., 2016; Dicka et al., 2019).

Another crucial point in analysing the concept of rurality is how to adopt a methodology able to capture the most relevant components abovementioned. One of the most common methods is to use linear combinations of multiple variables or multiple factor score, including weighted and unweighted linear sums and averages (Leduc, 1977; Cleland, 1995; Kralj, 2009; Cohen et al., 2017). Among these studies, Cleland (1995) equally weights factors like access to metropolitan areas, population density, percentage of employment in retail trade, percentage in public services, median family income, persistence of poverty and so on. Cohen et al. (2017), instead, use unweighted averages of variables like log of population density, log of population size, percentage of urban residents and inverse county distance to the closest metropolitan areas. Nevertheless, the majority of the studies adopt techniques such as Principal Component Analysis (PCA), factor analysis and cluster analysis; often combined to each other. The first work that uses PCA technique is Smith and Parvin (1973). Here, nine components concur in the construction of rurality index: population density, percentage of people living in rural areas, total population, percentage of employment in agriculture, percentage people living on farms, average annual percentage change in population, percentage employment in medical and dental professions, percentage employment in entertainment and recreation services, percentage employment in service work. However, the most popular paper that adopted PCA in agricultural context is Cloke (1977). The author develops an index of rurality for Wales and England. Many studies use PCA and/or cluster analysis to describe rural character of regions rather than developing an index of rurality. Other studies adopt tools of spatial analysis such as network analysis, density analysis, land cover techniques and proximity analysis. In this last case, researchers compute distances from urban centres, travel time to place of employment and access to nearest hospital. For instance, Cromartie et al. (2013) calculate travel time from each place to the edge of urban areas using network analysis. Other works (e.g. Mao et al., 2018; Mountrakis et al., 2005) use density analysis to examine access and availability of services and infrastructure, while other recent studies (e.g. Hoffmann et al., 2017; Nong, 2015) employ land cover analysis of sensed imagery for evaluating the diffusion of developed and undeveloped land cover.

Other techniques include more complex statistical tools such as fuzzy inference (Romano et al., 2016; Pagliacci, 2016) and neural network taxonomy (Paszto et al., 2015). For instance, as described in more details in Section 4, Pagliacci (2016) proposes a multidimensional and continuous indicator of rurality (Fuzzy Rurality Indicator) for 1300 NUTS3 regions in Europe.

As it is possible to understand from the abovementioned literature, the debate is about how defining properly the concept of rurality. For the time being, a unique and shared definition does not exist at international level (Montresor, 2002; Anania and Tenuta, 2008). This shortcoming is due to the heterogeneity of European territory in terms of socio-economic, environmental and demographic conditions across EU rural areas (European Commission, 2006; Copus et al., 2008). Nevertheless, since the 90s, relevant steps forward in defining a homogenous definition of rurality have been done and some criteria are widely accepted. The most well-known approaches are the Eurostat (Eurostat, 2010) and the OECD (1994; 1996; 2006) ones. Both urban-rural typologies are similarly based on population density and on distance from the major urban areas. According to these methodologies, NUTS 3 regions in EU Member States are classified as predominantly urban (PU), intermediate (IR) and predominantly rural (PR).

This unidimensional approach suffers from a great drawback: rurality is measured using a single indicator (e.g., population density) which captures only one aspect and surely not the polymorphism of different rural territories within EU Member States. Nevertheless, the OECD has tried to launch new strands of research with the aim of creating new and more understandable measures of rurality based on a set of variables (FAO-OECD Report, 2007; The Wye Group, 2007).

This constitutes a first step towards the idea that a multidimensional approach is more appropriate in the identification of a shared definition of rurality (Camaioni et al., 2013). The wide set of variables ranges from socio-demographics (e.g. population density) and sector-based variables (e.g. GVA in agriculture) to geographical features (e.g. land use, distance from metropolitan areas, services accessibility). Copus et al. (2008) review major multidimensional rural-urban typologies using a broad set of variables.

It is possible to divide studies about rurality taxonomy in EU Member States in different typologies. The first category regards the strand of literature that focus on one single or some specific regions within country. Cloke (1977) adopts Principal Component Analysis to build an index of rurality for England and Wales. The author considers variables such as population density, percentage of the residents working in another local authority area and percentage of males working in primary rural industries in 1971. Successively, Cloke and Edwards (1985) replicate the abovementioned study using data for 1981 and make a comparison with the previous index showing spatial differences in rurality taxonomy. Barjak (2001) adopts cluster analysis based on economic determinants for Poland and East Germany. The author demonstrates a strong link among largest agglomerations, high income, low unemployment and qualified labour force fostering technical progress.

Auber et al. (2006) apply PCA to define rural areas in France, while Merlo et al. (1992) and Anania and Tenuta (2008) focus on Italian cases. For instance, these last two authors find two interesting results. Firstly, no linkage between rural areas to "poverty" and urban areas to "higher incomes" has been found. The second aspect regards the fact that urban and rural municipalities are distributed everywhere within the country. By contrast, income per capita and levels of consumption differs a lot from one region to another one. Balestrieri (2014) shows the results of a multivariate analysis of municipalities of region Sardinia in Italy based on levels of rurality/urbanity and competitiveness which are proxied by two different sets of indicators. Buesa et al. (2006) elaborate the Spanish R&D system through factorial analysis applied on the university, the Public Administration, private enterprises and the regional production and innovation environment. The authors find out that Madrid stands out for public administration, Catalonia and Basque Countries excel for environment and private enterprises, respectively, and Navarra distinguishes itself for University. Furthermore, researchers show (through regression analysis) that the Regional Production and Innovation Environment is the most important factor compared to the other three for innovation purposes. Relying on data from Population Census 2001, Lowe and Ward (2009) define rural areas in UK applying a factor analysis to more than 100 socio-economic variables (e.g. commuting, demographic and deprivation indicators). They point out seven countryside typologies: "dynamic commuter areas" in the South East; "settled commuter areas” mostly corresponding to city regions; “dynamic rural areas” associated to research/universities centres; “deep rural areas” characterized by high level of tourism activity; “retirement retreat” with a high rate of ageing population; “peripheral amenity areas” sited on coastal areas with a high tourism and retirement activities; “transient rural areas” close to urban centres with low income level and high commuting levels.

The second strand of literature is that focuses specifically on EU Member States. Terluin et al. (1995) develop an agricultural typology based on the relationship between regional GDP per capita and farm net value added per annual work unit in order to analyse agricultural income situation in less developed areas (LFA) of EU12 in three different period (1987-1988, 1988-1989 and 1989-1990). The authors indicate three areas (Northwest, Central and South) and show that the income gap is larger in the two former areas rather than in the latter and that farm income level in Northwest and Central is notably greater than in the South. Ballas et al. (2003) propose a rurality typology in EU by employing both principal component and cluster analysis on data for NUTS3 regions based on their peripherality. The authors note this proposed typology identifies national differences in particular for smaller Member States like Portugal and Greece. Nevertheless, they also argue that this taxonomy presents drawbacks and should be used only as an approximation of reality and as a starting point for further analysis. Vidal et al. (2001) use NUTS3 level data from Eurostat (except for Germany, Belgium and the Netherlands where data are at NUTS2) to highlight spatial determinants of EU rural areas in agricultural sector. The researchers adopt a principal component analysis and a hierarchical (k-means algorithm) cluster analysis on a set of variables covering different dimensions such as economic activity, demography, agricultural employment and land use, farm structure and labour force. This classification shows the heterogeneity of EU rural areas. Macro and micro-scale dimensions developing three aspects of rural differentiation are proposed by Copus et al. (2011) in the context of the EPSON project EDORA. The first feature is “Rurality and Accessibility” which pertains with DG Regio taxonomy: ‘intermediate accessible’, ‘intermediate remote’, ‘predominantly rural accessible’ and ‘predominantly rural remote’ (Dijkstra and Poelman, 2008). The second aspect is the so-called “Economic Restructuring” which relates to both the Agri-Centric and Global Competition classifications and differentiates the rural EU regions in ‘agrarian’, ‘consumption countryside’, ‘diversified’ (strong secondary sector) and ‘diversified’ (strong market services sector). Thirdly, “Performance” is a category that places EU regions on a continuum between ‘accumulation’ and ‘depletion’ and mainly follows DG Regio’s rural-urban taxonomy. The consequent categories are ‘accumulating’, ‘above average’, ‘below average’ and ‘depleting’. Raggi et al. (2013) suggests a multidimensional classification of 1303 NUTS3 regions based on four criteria: accessibility, economic diversification, GDP per capita and rural character. The paper’s aim is to compare rural development policy impact among regions across EU. Three different approaches emerge: traditional cluster analysis, latent class models and multiple cluster structures. Esposti et al. (2013) proposes a new composite indicator of rurality and peripherality based on NUTS3 level data. The authors create the “PeripheRurality” indicator (PRI) using principal component analysis which takes into consideration both socio-economic and geographical variables. Moreover, the researchers study the link between the Rural Development Programme (RDP) expenditure in each cluster and the PRI using correlation coefficients. Pagliacci (2016) use fuzzy logic methodology to create a multidimensional and continuous indicator of rurality. The author covers the EU 28 NUTS3 regions and uses several variables that include not only demographic dimension but also the sector-based approach and the territorial approach. The novelty of this work lies in the methodology: a fuzzy indicator is a better way of describing rural-urban continuum with respect to OECD-Eurostat taxonomy because it has all properties of continuous indicators. Pagliacci argues that this indicator returns a more detailed picture of EU rural-urban situation and it is more accurate in describing rurality level compared to OECD and Eurostat’s classifications.

Finally, literature review of papers focusing on OECD countries are briefly reported. Bollman et al. (2005) examine differences in employment growth using the OECD taxonomy in the 1900s for 14 OECD countries. Furthermore, they measure employment rate trend between the 1980s and 1990s. For this purpose, they rank regions in each country in three groups according to their employment growth rate. Successively, the researchers make a comparison among the ranking position of the same regions in the 1980s and in the 1990s. The results show that in the predominantly rural and intermediate rural regions in the 1990s employment growth rate exceeds with respect to predominantly urban areas, that is a common trend from the 1980s.

As previously said, rurality is a not-precisely defined concept. The existing classifications are built on a single indicator such as demographic density and distinguish between predominantly urban (PU), intermediate (IR) and predominantly rural (PR) regions. The main risk of this approach lies in classifying dissimilar regions in the same group. For this reason, the applied literature has developed many rurality typologies and further research is needed.

3. Data

Variables refer to the EU 28 Member States and rely on EUROSTAT, ARDECO and Corine Land Cover datasets. The choice of input variables is based on post-industrial rurality model (Sotte et al., 2012). Considering NUTS3 granularity fosters comparison among different rural-urban taxonomies as both Eurostat and OECD are built at this geographical level of aggregation[1]. This study adopts NUTS 2016 version and counts 1062 regions at NUTS3 level. As it will deepen in methodology section and following Pagliacci (2016), fuzzy tree is constructed upon six variables, proxying three thematic areas. The first area follows a sector-based approach. Therefore, the three variables that represent the role of agriculture are GVA in agriculture, employment in agriculture and surface of agricultural land. The first two variables are collected from ARDECO database, which is produced by DG REGIO. While, surface of agricultural land comes from Corine Land Cover (CLC) database, which combines national agencies information and is coordinated by European Environmental Agency (EEA), and then, it is harmonized with Eurostat data. The second area follows the OECD-EUROSTAT methodology and represents the demographic approach. Thus, it is proxied by population density. The third field follows the territorial approach and focuses on landscape and land use. In this case, the two considered variables are surface of forested areas and surface of artificial areas, and they are taken once again from Corine Land Cover database. The reference year for all variables is 2018 and it is chosen because is the latest available at the moment this paper is written. Furthermore, in the 2016 the *Greening Reform* of the Common Agricultural Policy (CAP) has been implemented. This reform is particularly relevant for rural areas in European Union because it marks a key moment that induces changes in Member States' implementation choices. Among other things, this reform is characterized by a reduction in Pillar 1 and Pillar 2 expenditures and by increasing payments to environmental measures (Montezuma et al., 2021). Table 1 reports summary statistics for all variables involved in the empirical analysis. As far as the agricultural dimension is concerned, three variables are considered. First, *GVA in Agriculture* which is gross value added in agricultural sector expressed in million euro PPS[2]. The

[1] For all countries information are at NUTS3 level, except for Germany where data have been aggregated at NUT2 level because of their small dimension.

[2] PPS stands for Purchasing Power Standard. It is an artificial currency unit. One PPS can buy the same amount of goods and services in each country. PPS are derived by dividing any economic aggregate of a country in national currency by its respective PPP. PPP can be interpreted as the exchange rate of the PPS against the Euro. Source: EUROSTAT (https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Purchasing_power_standard_(PPS))

second agricultural variable is *Employment in Agriculture* which is represented by thousands of employed persons in the primary sector. *Agricultural Land* is the third agricultural variable and represents the land surface expressed in km^2 designed to agricultural use. The demographic approach is proxied by *Population density* which is defined as the number of people living per unit of land area (in km^2). Finally, landscape dimension is built on two variables. The former is *Forested Land* which is surface covered by forests and other semi-natural areas expressed in km^2; while the latter is *Artificial Land* which consists in surface covered by artificial areas (urban fabric, industrial and commercial units…) in km^2. Unlike in Pagliacci (2016), all the data considered in this study are absolute values instead of shares. However, the appendix reports the analysis taking into account variables in relative terms and results slightly change due to the fact that variables in the main estimations were still normalized.

Table 1: Summary Statistics

	Mean	Median	Maximum	Minimum	St. dev
GVA in agriculture	220,9798	136,788	2446,002	0,0159	263,9091
Employment in agriculture	9,644	5,324	159,138	-0,204	13,65801
Agricultural areas	1871,5	1163,7	15865,2	0	2095,012
Population density	681	146,2	21043,6	1,9	1662,755
Forested areas	1831,4	784,2	84269	0	4689,182
Artificial areas	208,16	154,99	2137,89	6,99	189,0395

Notes: *GVA in Agriculture* is gross value added in agricultural sector expressed in million euro PPS. *Employment in Agriculture* is represented by thousands of employed persons in the primary sector. *Agricultural Areas* represents the land surface expressed in km^2 designed to agricultural use. *Population density* is defined as the number of people living per unit of land area (in km^2). *Forested areas* is surface covered by forests and other semi-natural areas expressed in km^2. *Artificial areas* consists in surface covered by artificial areas (urban fabric, industrial and commercial units. . .) in km^2.

4. Methodology

Fuzzy Logic (FL) was first presented in the 1960s, as an extension of Boolean logic (Zadeh 1965, 1968, 1975). The interesting feature of this method consists in reproducing human way of reasoning: clear cut-offs to classify observations within well-defined classes do not exist. By contrast, Fuzzy Logic introduces the notion of degree in conditions verification. This means that each observation is linked to its probability of belonging to a given class. Furthermore, this methodology refuses the Boolean algebra based on a binary logic according to which sentences can be either true or false. Contrary, FL deals with the concept of partial truth: any sentences may vary from completely true to completely false. Precisely, this feature affects the way to construct membership functions. Indeed, co-domain of membership function ranges in a set of values within the closed interval [0,1]. Let's give a denotation of the phenomenon. Let X represents all possible objects, a fuzzy set called $A \in X$ can be defined as a set of ordered pairs, such as: $A = \{(x, \mu\_A\ (x)) : x \in A, \mu\_A\ (x) \in [0,1]\}$. $\mu\_A\ (x)$ is the membership function of the fuzzy set A which associates each object x to a value in the interval [0,1]. If $\mu_A(x) = 0$, x is not a member of A, whereas, if $\mu_A(x) = 1$ x is completely associated to the set A. The third scenario is that the object is included within the interval [0,1] and belongs to the set A according to some grade. Therefore, observations may partially belong to a given set. For instance, let's the variable $Z_1 =$ "$cold$" "*cold*" with the degree μ =0,8 this means that the variable has a linguistic value represented by the label "*cold*", whose meaning is determined by the degree of 0,8.

Furthermore, Fuzzy Logic takes advantage in adopting decision trees: complex decisions are split into simpler decision-processes. As Zadeh (1975) suggests, rules are set by means of linguistic variables: this process fits particularly well for those variables "whose values are not numbers but words or sentences in a natural language".

Finally, three elements build the inferential system. The first one is a decision tree which links a list of input variables to the output. The second element is the membership function. The last components are logical and mathematic operators which generate inference and quantitative rules. Fuzzy logic follows a precise procedure, and six fundamental steps can be disentangled. First, the most suitable fuzzy system is designed. The second phase consists in the fuzzification of the inputs, that means, for instance, transforming original crisp values[3] into fuzzy numbers, according to specific linguistic (i.e., qualitative) terms and a given membership function. The third step is to define the *if-then rules* and to apply logical operators. Then, inference is computed through aggregation of the so-called ‘antecedent’ to the ‘consequent’. The successive step is the aggregation of the output (i.e., the consequent). Finally, the last step consists in the defuzzification, which means converting fuzzy numbers into crisp values.

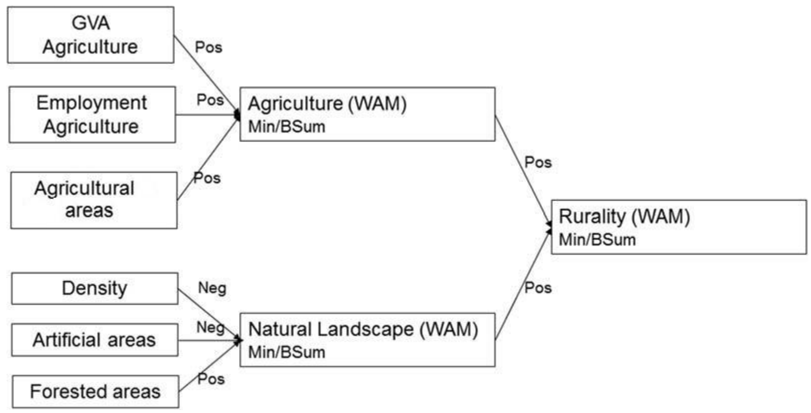
An element of concern is the appropriateness of this approach to the case under study. In literature, FL seems to be feasible for describing problems with regional dimension (Hall & Arnberg, 2002; Arnot & Fisher, 2007). Also fuzzy cluster analysis can be adopted: it computes grades of membership within each cluster. For instance, Taylor & Derubber (2004) adopt this technique to describe different typologies of EU cities.

Fuzzy Logic fits well when at least one of the following conditions is verified. Existence of ambiguity is the first situation that must occur (i.e., the case in which continuous data that do not belong neatly to discrete class). Then, FL suits when there is spatial vagueness. For instance, either it is difficult to identify boundary location or some gradual transitions are proved among classes. Finally, Fuzzy Logic is preferred when its outcomes interpretation is clearer than other taxonomies’ one. In this work, all these three conditions occur. Firstly, the existence of a foggy rural-urban continuum to measure constitutes the element of ambiguity. Second, also spatial vagueness is confirmed due to NUTS3 regions boundaries which are defined according to historical and administrative motives and largely differ across EU Member States. Finally, results from Fuzzy Logic analysis are easily interpretable.

As shown in Figure 1, the fuzzy tree is built on the six abovementioned inputs. The figure highlights relationships between inputs and intermediate outputs and between intermediate outputs and final output. The three sector-based variables produce “role of agriculture” intermediate indicator; while population density and land use inputs create “natural landscape” intermediate indicator. As far as natural landscape output is concerned, the idea is that the three inputs (population density, forested and artificial land) could represent how much human activity and settlements have shaped natural environment. Then, the two intermediate outputs become inputs for creating the final output which is the FRI, Fuzzy Rurality Indicator.

[3] A crisp value is the same as Boolean value (either 0 or 1). Either a statement is true (1) or it is not (0).

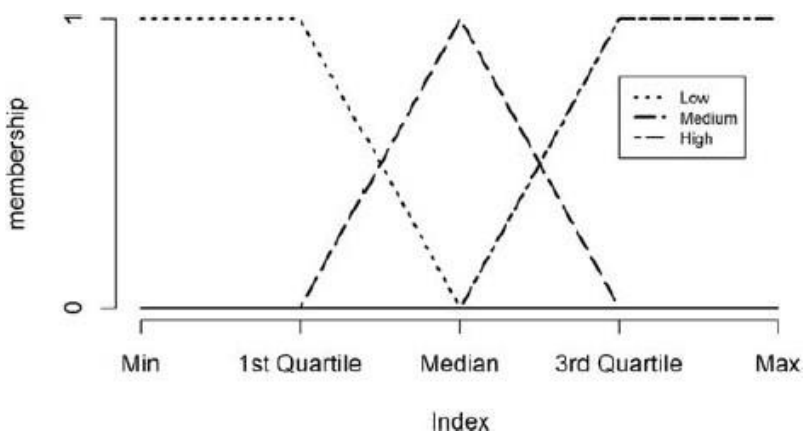
Figure 1: Fuzzy decision tree and signs of relationship



Notes: The figure highlights relationships between inputs and intermediate outputs and between intermediate outputs and final output. Source: Author's elaboration from Pagliacci (2017)

Once fuzzy system is built, fuzzification phase begins. Input, intermediate and final output are real numbers; whereas fuzzy numbers, which define the relationships between inputs and outputs, do not assume crisp values. Therefore, fuzzification's aim is to transform inputs into degree of membership function according to linguistic terms of fuzzy sets. In this work, three ordinal values describe each input: "low", "medium" and "high". Membership functions are functions of real numbers which range from 0 to 1 (where 0 means "no membership" and 1 indicates "complete membership") and transform crisp values into fuzzy variables (Murat & Pirotti, 2010). Each membership function has its own shape. Usually, the most common shape of membership functions are triangles and trapezoids: three points for triangle and four points for trapezoid. As it is possible to observe in the Figure 2, membership functions correspond to figures in a cartesian plane where the x-axis stands for variable level and the y-axis represents the value assumed by the membership function for that level (from 0 to 1). In this work, the simplest assumption is adopted: for each input, membership function is just formed through its quartile distribution (1^{st} quartile, median and 3^{rd} quartile). Figure 2 gives an example of membership function.

Figure 2: Example of membership function



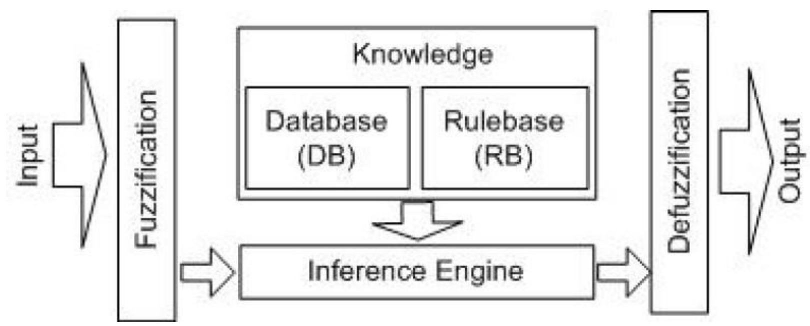
Notes: Figure gives an example of membership function. In this work, for each input, membership function is just formed through its quartile distribution (1st quartile, median, 3rd quartile) Source: Pagliacci (2017)

After fuzzification phase, rule blocks are set. Eventually, they are expressed in the form "*IF-THEN*". The IF-part (antecedent) characterizes a specific situation; the THEN-part (consequent) represents the response of fuzzy system given that condition. Inference is allowed thanks to rules that transform inputs into a single output. The fuzzy inference (fourth phase) works with different methods of aggregation. In this case, for the IF-part is used the *MIN operator* method to aggregate input of rule blocks; while, for the THEN-part, the *Bounded Sum* (BSUM) is adopted for the aggregation of the results. The BSUM operator applies the sum of all values up to one (which is the maximum value that can be assumed). In this model, all inputs have the same weight in defining outputs because the aim of this work is to build a synthetic urban-rural indicator that considers all inputs equally. As the rule blocks show in the appendix, three qualitative categories (low, medium and high) describe each input; intermediate and final output are defined by five (very low, low, medium, high, very high) and seven (very low, low, medium-low, medium, medium-high, high, very high) grades, respectively. This differentiation is relevant because it properly highlights EU Member States heterogeneity. With respect to the structure of the rule, there exists two Fuzzy Rule-Based Systems (frbs) models: the Mamdani and the TSK model. In this work, the Mamdani model is applied. It is constructed by linguistic variables in both the antecedent and consequent parts of the rules. Thus, considering multi-input and single-output (MISO) systems, fuzzy IF-THEN rules are set as:

$$IF\ X\_1\ \ is\ A\_1\ \ and\ \dots and\ X\_n\ \ is\ A\_n\ \ THEN\ Y\ is\ B,$$

where X_1 and Y are input and output linguistic variables, respectively, and A and B are linguistic values. The standard structure of this model is represented in the Figure 3 and consists in four elements: fuzzification, knowledge base, inference engine and defuzzifer (Riza et al., 2015). The "Knowledge" block is composed of two elements: a database and a rulebase. The former contains the fuzzy set definitions and the parameters of the membership functions, while the latter includes the set of IF-THEN rules. The "inference engine" carries out reasoning operations on proper fuzzy rules and input data. Finally, defuzzification phase takes place. It occurs by means of Weighted Average Method (WAM) for intermediate and final output. The defuzzifier produces the final output transforming fuzzy numbers into crisp values from linguistic values.

Figure 3: The components of Mandami model



Notes: The structure of Mandami Model is composed of four elements: fuzzification, knowledge base, inference engine and defuzzifer. Source: Riza et al. (2015)

5. Results

5.1 Main results

The contribution of this work is twofold. First, a new indicator to describe the degree of rurality is calculated whose aim is to give a more nuanced picture of rural-urban continuum. Secondly, the benefit of this index consists in deriving a new taxonomy which constitutes an alternative to the existing ones.

The Fuzzy Rurality Indicator provides a synthetic way to measure rurality, considering both the role of agriculture and the status of natural landscape. These intermediate outputs try to explain rural characteristics throughout European Union. The aim of the analysis is to compare the FRI to other rural-urban taxonomies, like the Eurostat one, and to observe what changes taking into account different criteria to establish a degree of rurality. As illustrated in the methodology section, Fuzzy Logic finally provides the output, the FRI, which ranges from zero to one. Zero stands for completely urban, while one means completely rural. For the sake of simplicity, following Pagliacci (2016), four categories are disentangled. When FRI is smaller or equal to 0,25, regions are classified as *urban*; if FRI is included between 0,25 and 0,50 (or equal to 0,50) the region is *slightly urban*; regions with a FRI included in the interval 0,50 and 0,75 are *slightly rural*; finally, when FRI is strictly larger than 0,75 regions are categorized as *rural*. In Table 2, number of EU 28 NUTS3 regions that fall into each class is reported, both for the two intermediate and final outputs.

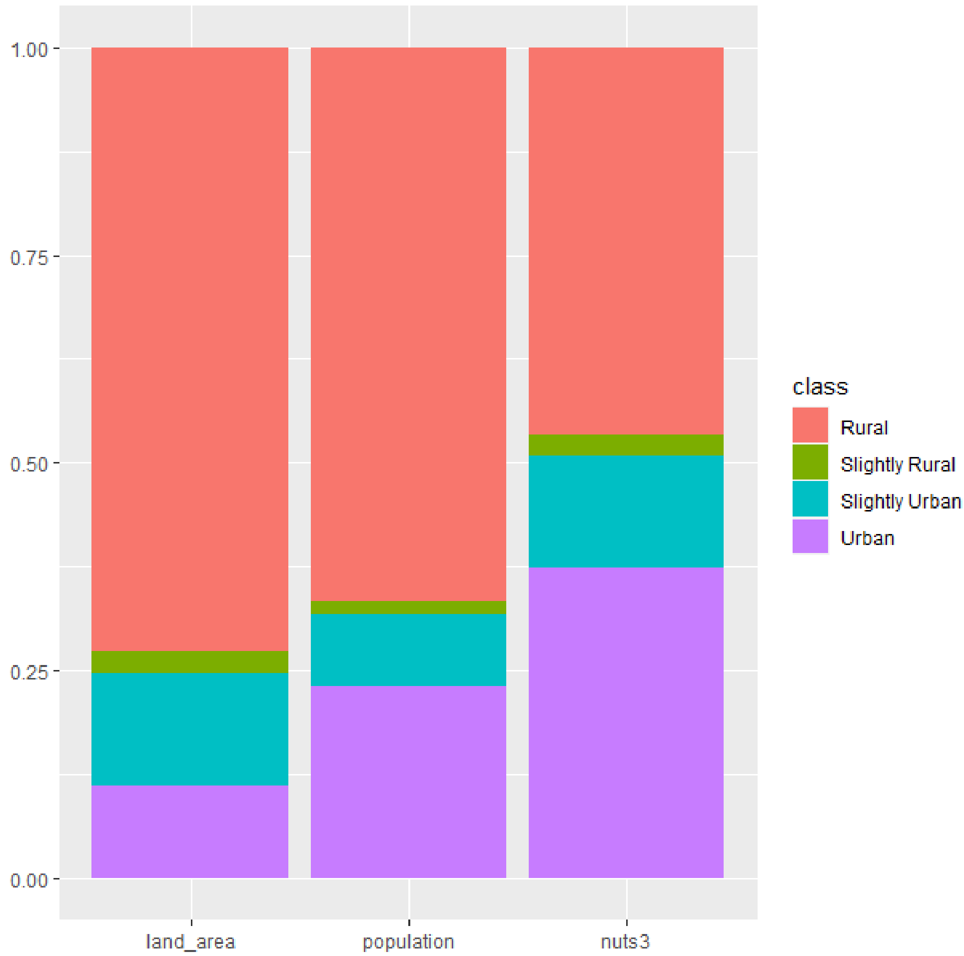
Table 2: Intermediate and output indicators

Class	Role of Agriculture	Natural Landscape	FRI
Urban regions	467	346	402
Slightly urban regions	179	250	125
Slightly rural regions	43	99	41
Rural regions	373	367	494

Notes: Table reports NUTS-3 regions falling into each class. If FRI is smaller or equal to 0,25, regions are classified as urban; if FRI is included between 0,25 and 0,50 (or equal to 0,50) the region is slightly urban; regions with a FRI included in the interval 0,50 and 0,75 are slightly rural; finally, when FRI is strictly larger than 0,75 regions are categorized as rural.

Distribution across classes is bell-shaped: regions in the “middle” (i.e., *slightly rural* and *slightly urban*) are less crowded than regions in the two extreme ones. However, incorporating rural to slightly rural and urban to slightly urban regions respectively, it is possible to observe a more homogenous regions’ distribution within each category. NUTS3 regions falling into rural category is 50.3% against the 49.7% of urban regions. Thus, it is possible to state that EU 28 is quite balanced territory at first glance. Nonetheless, this result could be misleading to identify rurality among Member States. Therefore, it could be useful to consider rurality also in relation to share of population and land area, as it is summed up in Figure 4. Looking at FRI classification in terms of land area, the picture described above slightly changes. In fact, rural regions (where FRI > 0.75) cover about 3,1 million km^2 which corresponds to 72.6 % out of total EU land area (data here refer to 1062 NUTS3 regions under consideration). While urban regions (FRI <0.25) represent about 11.1% that means 489 thousand km^2. An interesting insight is the comparison with Pagliacci’s classification that shows a lower percentage of rural regions in terms of land area (56.3%). Generally, it follows that EU 28 is mainly a rural territory. The importance of EU rural space has been too frequently underestimated. Instead, this result highlights the need to better identify EU-28 Member States’ rural characteristics in order to address precise policy implications. A similar result is found analysing the FRI in terms of population. In fact, almost 180 million people live in rural areas (about 66.6% out of total population in European Union member states taken in consideration). Conversely, only 62 million citizens are classified as living in urban areas which corresponds to almost 23.1% of total population. Again, this finding largely differs with respect to Pagliacci (2016) that classified about 40% of people as urban and almost 23.6% as rural. In addition, regions which show mixed rural-urban features play an important role confirming the relevance of the rural-urban continuum. They count for 16.2% and 10.2% in terms of land area and population, respectively.

Figure 4: Land area, population and number of regions by FRI class (EU-28)



Notes: the figure illustrates the percentage of regions falling in the four classes both in absolute values and in relation to land area and population. Source: author's calculation.

Even if both this analysis and Pagliacci (2016) adopt the same methodology to extract information, a plausible reason that justify these discrepancies between the two classifications could lay in the year reference choice and in the considered variables.

The second relevant insight that emerges from this analysis regards European heterogeneity. In fact, looking at the FRI reveals the importance that rural areas assume in driving policy decisions. The study highlights great differences among Member States. Table 3 shows average values of both intermediate and FRI output by each country.

Table 3: Intermediate outputs and FRI. Average values by Member States

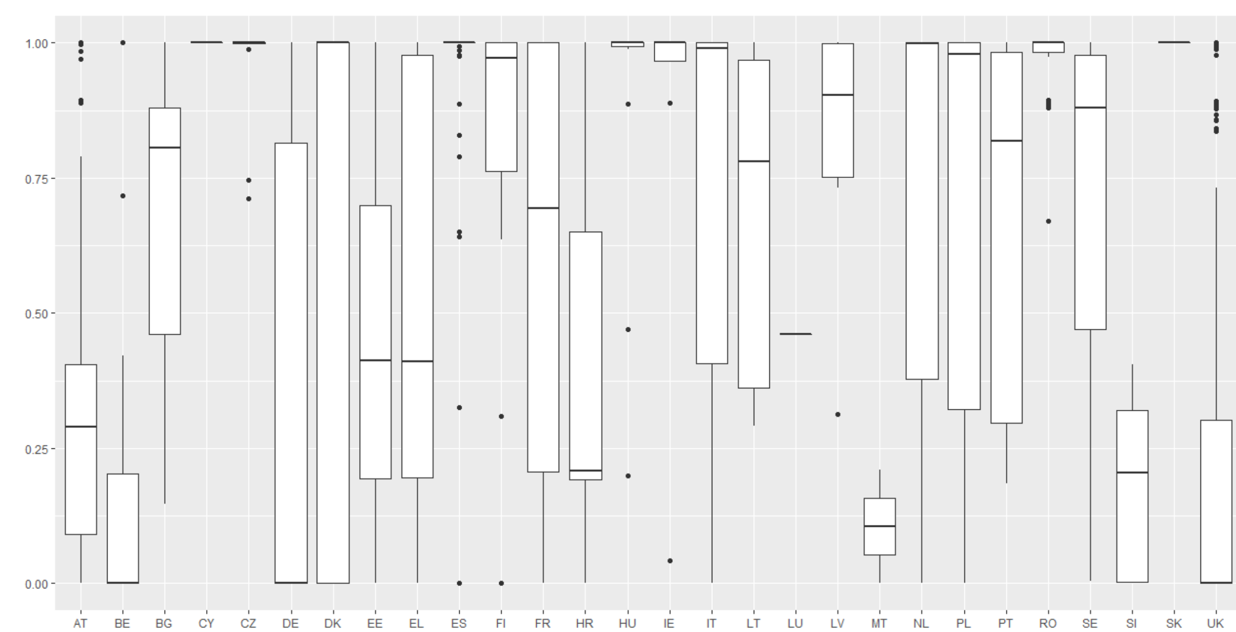
Country	Average Role of Agriculture	Average Natural Landscape	Average FRI
Austria	0.231804494	0.58851413	0.33869933
Belgium	0.079523829	0.617755652	0.1288358
Bulgaria	0.409598221	0.386715636	0.68192215
Croatia	0.25559925	0.785826402	0.40229118
Cyprus	1	0	1
Czechia	0.883807516	0.059630227	0.96022994
Denmark	0.547618487	0.200800539	0.56127592
Estonia	0.340856022	0.296641629	0.46097911
Finland	0.673779078	0.349236316	0.83352691
France	0.47811259	0.202563221	0.58399509
Germany	0.262313508	0.577295393	0.30075079
Greece	0.387433962	0.865362939	0.52281192
Hungary	0.864270751	0.142877402	0.92631685
Ireland	0.796715419	0.3244667	0.86556858
Italy	0.638504692	0.626339386	0.74832356
Latvia	0.623861124	0.308036538	0.80855153
Lithuania	0.513380123	0.339240582	0.6792823
Luxembourg	0.33153141	0	0.46121972
Malta	0.050263777	1	0.10462563
Netherland	0.657710548	0.658107842	0.73248879
Poland	0.613029471	0.20505827	0.72561629
Portugal	0.465961322	0.671391837	0.64903685
Romania	0.858149785	0.115167742	0.97059797
Slovakia	1	0.010689165	1
Slovenia	0.109047283	0.926570119	0.16952506
Spain	0.868546382	0.350743512	0.92111974
Sweden	0.499062248	0.221819406	0.70998313
United Kingdom	0.143916707	0.706653967	0.21308102

Notes: table reports the average values for the two intermediate outputs, *Role of Agriculture* and *Natural Landscape* and for the final output, the *FRI*, for each Member State.

The lowest values for the role of agriculture are recorded in the United Kingdom, Slovenia, Malta and Belgium. By contrast, highest values for this intermediate output affect Slovakia, Spain, Czechia and Romania. As far as the average landscape values are concerned, largest figures occur for Slovenia, Malta and Greece, specifically, South-Eastern Member States. Opposite, lowest figures involve Luxembourg, Czechia and Slovakia. Looking at FRI, results present a clear picture: most Eastern countries such as Hungary, Romania and Czechia are the most rural part of EU-28. In addition, Spain highlights this trend. On the other hand, UK, Malta and Belgium are mostly urban countries.

Furthermore, each Member State presents different characteristics within own boundaries. In fact, Figure 5 illustrates FRI distribution at national level. This type of graph is useful because it allows studying also the sub-national differences[4]. On the one hand, countries that shows mostly rural or mostly urban features register little differences in terms of rurality within country. This group includes Hungary, Slovakia and Malta. On the other hand, other Member States like Denmark, the Netherlands and Portugal show a continuous urban-rural distribution at NUTS3 level.

Figure 5: FRI distribution within each Member States

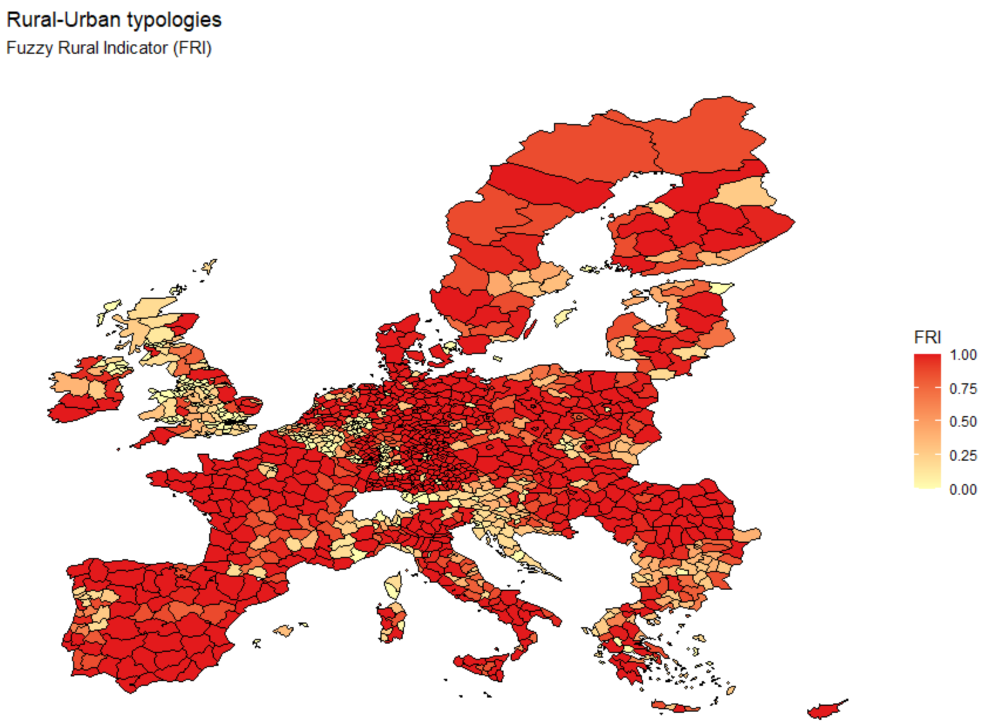


Notes: the boxplot represents the FRI distribution across the EU-28 Member States. It highlights the territorial heterogeneity within European countries. Source: author's calculation.

[4] In any boxplot, five elements are visualized: the minimum, the maximum, the median, the first and the third quartiles. In this case, edges of the box are first and third quartile of national FRI distribution, respectively. Bar inside the box represents the median value. Whiskers stretch to the most extreme points (minimum and maximum) excluding outliers. To construct the boxplot usually the interquartile range (IQR) is adopted: the boundaries of the whiskers are included within the 1,5 IQR value. Observations excluded from the whiskers are outliers of the distribution (here, plotted as bold dot).

Another interesting representation is the map that describes in detail the rural-urban continuum throughout EU 28 at NUTS3 level, which is the level of data aggregation for this study. This represents an element of innovation with respect to previous studies where only single countries are mapped (e.g. in Pagliacci 2016). Here, colour blends from light yellow to dark red according to the level of rurality for each NUTS3 region. The map in Figure 6 is insightful to provide at first glance picture of EU-28 rural-urban continuum.

Figure 6: NUTS3 regions by FRI across EU-28



Notes: the map shows the distribution of NUTS-3 regions in terms of FRI across EU-28. FRI varies from 0 (=*Urban*) to 1 (=*Rural*). Colour blends from light yellow to dark red according to the level of rurality for each NUTS-3 region. Source: author's calculation.

What it is stressed in this study is the importance to suggest an innovative rural-urban classification which differs from the traditional ones (e.g., EUROSTAT). This aspect is relevant because it has policy implications and drives political choices. For instance, the evaluation of Rural Development

Programme (RDP)[5] both ex-ante through a SWOT analysis and ex-post through CIE methods could largely take advantage from a proper rural-urban identification. The optimal funds allocation could help more polarized MSs to improve territorial cohesion and rebalance the gap between urban centres and more remote regions within the country. On the other hand, Member States that show a more balanced situation could use funds to foster sustainable integration among different regions and could contain the urbanisation inside intermediate areas (safeguarding environment in those areas). To sum up, a more accurate definition of rural-urban typologies could help policy makers (Barca et al., 2012).

Finally, the last purpose of this study is comparing two different rural-urban typologies. FRI categories are analysed in relation to Eurostat typologies. Eurostat methodology takes into consideration only population density and distinguishes predominantly urban (PU), intermediate (IR) and predominantly rural (PR) regions. This classification categories as predominantly urban those regions where more than 80% of the population live in urban clusters; intermediate regions as those regions where more than 50% and up to 80% of the population live in urban clusters; predominately rural regions as those regions where at least 50% of the population live in rural grid cells[6]. The aim of the FRI is to improve the existing taxonomy and give a wider picture of EU rural-urban continuum.

What emerges from the analysis is quite surprising and it is well represented in Figure 7. In principle, one would expect regions classified as "*urban*" in the Eurostat taxonomy to be categorized as "*urban"* (or at least, "*slightly urban"*) according to FRI and, vice versa, "*rural*" regions to be categorized as "*predominantly rural*". On the contrary, the scenario is very different with respect to the expectations. What is observed is a homogeneous regions' distribution throughout the three Eurostat categories. In fact, looking at the average FRI value for predominantly urban, predominantly rural and intermediate regions, very similar numbers are observed: 0.54, 0.52 and 0.50, respectively.

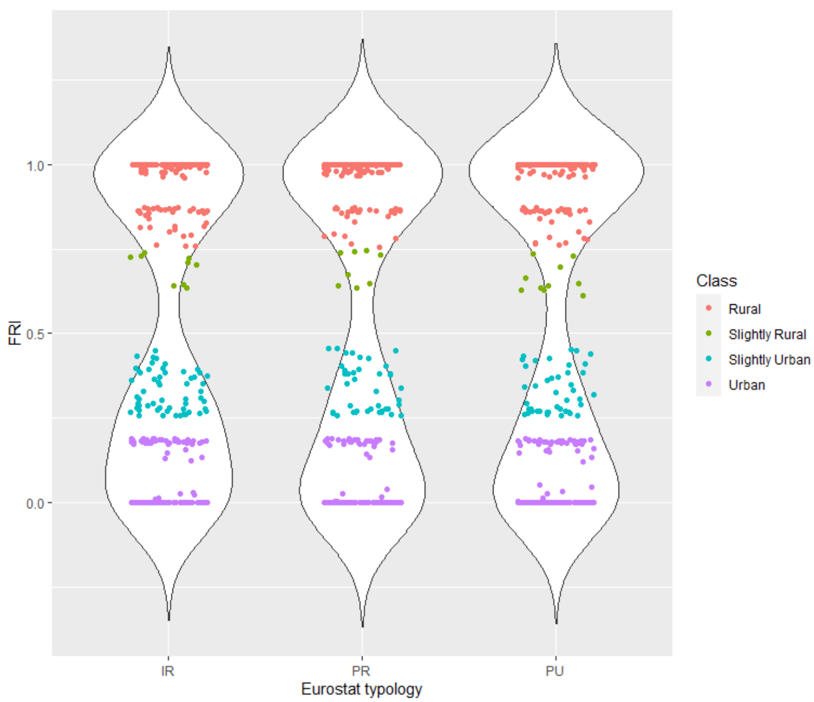
[5] EU countries implement European Agricultural Fund for Rural Development (EAFRD) funding through Rural Development Programmes (RDPs). RDPs are co-financed by national budgets and may be prepared on either a national or a regional basis. While the European Commission approves and monitors RDPs, decisions regarding the selection of projects and the granting of payments are handled by national and regional managing authorities. Art. 6 of Regulation (EU) No 1305/2013 represents the legal basis. Source: https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/rural-development_en

[6] Eurostat website: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Urban-rural_typology

Also in this case, findings largely differ in comparison to Pagliacci (2016) whose classification largely overlaps the Eurostat one: lowest FRI values correspond to predominantly urban regions and greater FRI values occur in predominantly rural regions. The plausible reason, once again, could be the difference in the year reference choice and the considered variables.

For a better understanding, Figure A2 in Appendix provides a graphical representation of the NUTS3 regions Eurostat classification.

Figure 7: Distribution NUTS3 regions by FRI values throughout Eurostat categories



Notes: the graph is a violin plot which, using density curves, depicts distributions of NUTS-3 regions throughout the four Eurostat's rural-urban categories. Source: author's calculation.

The last step of the study is to perform a one-way ANOVA (analysis of variance) whose aim is highlighting whether the differences observed in the average FRI have any statistical significance or not (mean comparison among groups). One of the main assumptions is homoscedasticity; therefore, Levene's test has been performed. It is possible to claim that all classes are significantly different in terms of FRI[7], as it is showed in Table 4. Another interesting insight regards ANOVA test performed on Eurostat rural-urban typologies: difference in the average FRI is not statistically significant. Once again, FRI appears more suitable than Eurostat methodology in dealing with rural-urban continuum. Table A5 is reported in the Appendix and represents the Turkey HSD test results Eurostat classification.

Table 4: Turkey DHS test results for FRI categories

Simultaneous Tests for General Linear Hypotheses
Multiple Comparisons of Means: Tukey Contrasts Linear Hypotheses:

	Estimate	Std. Error	t value	Pr(>|t|)
Slightly Rural - Rural == 0	-0.275844	0.011531	-23.92	<2e-16 ***
Slightly Urban - Rural == 0	-0.615690	0.007104	-86.67	<2e-16 ***
Urban - Rural == 0	-0.909859	0.004766	-190.92	<2e-16 ***
Slightly Urban - Slightly Rural == 0	-0.339846	0.012769	-26.61	<2e-16 ***
Urban - Slightly Rural == 0	-0.634015	0.011632	-54.51	<2e-16 ***
Urban - Slightly Urban == 0	-0.294169	0.007266	-40.49	<2e-16 ***

(Adjusted p values reported – single-step method)

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

5.2 Robustness checks

In this section, a robustness check is presented. The model is performed using variables expressed in relative terms. Generally, main results are confirmed and even reinforced.

The robustness check consists in replicating the analysis using variables in relative terms. Table 5 reports the number of NUTS3 regions falling into the four categories for the two intermediate outputs and for the final output FRI.

[7] In this case, the post-hoc Tukey HSD test is adopted to see which groups are different from the others.

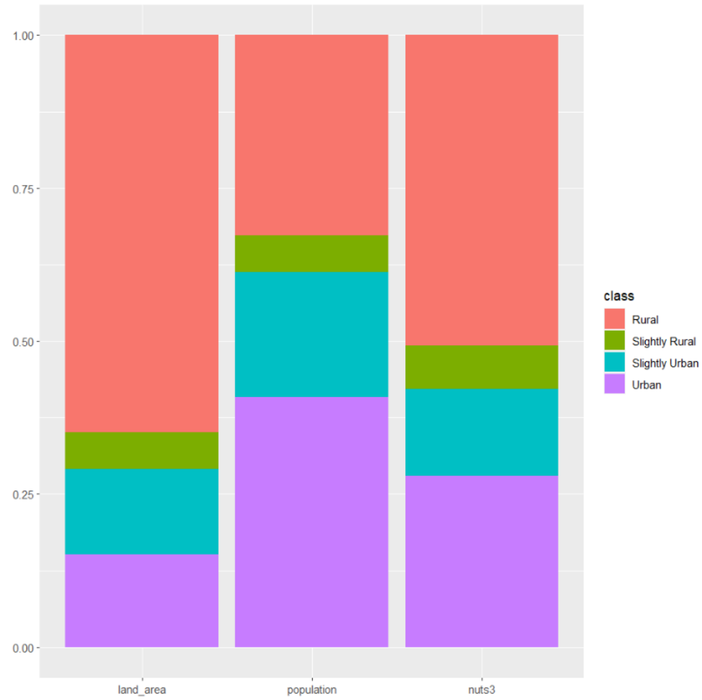
Table 5: Intermediate and output indicators

Class	Role of Agriculture	Natural Landscape	FRI
Urban regions	427	351	294
Slightly urban regions	231	198	151
Slightly rural regions	59	138	77
Rural regions	345	375	540

Notes: Table reports NUTS-3 regions falling into each class. If FRI is smaller or equal to 0,25, regions are classified as urban; if FRI is included between 0,25 and 0,50 (or equal to 0,50) the region is slightly urban; regions with a FRI included in the interval 0,50 and 0,75 are slightly rural; finally, when FRI is strictly larger than 0,75 regions are categorized as rural.

Overall, the main result is confirmed and even reinforced: EU-28 remains mainly a rural continent with some little changes in the composition of the four classes. In fact, if "*slightly*" regions are incorporated respectively to urban and rural regions, it is possible to observe a homogenous regions' distribution. Indeed, rural regions count for around 58% over the total of regions considered against about 42% of urban regions. Therefore, EU-28 seems a quite balanced territory. However, also in this case, it is insightful to consider rurality in terms of land area and population as showed in Figure 8. Firstly, looking at FRI in relation to land area, rural regions cover about 2.8 million km^2 which corresponds to about 65% out of the total EU land area. By contrast, urban regions represent almost 15% which means about 662 thousand km^2. Therefore, EU-28 is considerably a rural territory. However, the picture slightly changes when rurality is considered in terms of population. In fact, almost 110 million people live in urban areas against 89 million inhabitants who live in rural areas. Thus, considering the number of inhabitants, EU-28 appears a more urbanised continent. This simply means that EU countries tend to have a higher concentration of people in urban areas.

Figure 8: Land area, population and number of regions by FRI class (EU-28)



Notes: The figure illustrates the percentage of regions falling in the four classes both in absolute values and in relation to land area and population. Source: author's calculation.

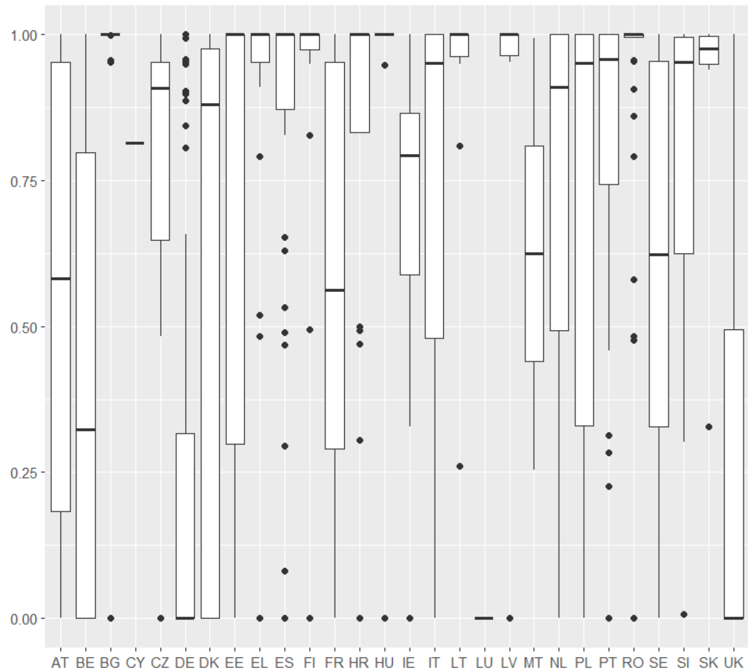
Furthermore, the main results are confirmed again when European heterogeneity is under analysis. The study highlights great differences both among and within Member States. Table 6 shows average values of both intermediate and FRI output by each country. Looking at FRI, the most rural countries are Bulgaria, Romania and Hungary as in the main analysis. By contrast, United Kingdom, Belgium and Germany are highlighted as the most urban countries. As it is possible to observe in Figure 9 representing FRI distribution at national level, territorial heterogeneity is also present within countries. Indeed, graph illustrates little differences with main results' distribution of FRI. Countries such as Hungary, Slovakia, and Romania, which predominantly exhibit rural characteristics, display minimal variations in terms of rurality within their borders. Conversely, countries like Denmark, the Netherlands, and Portugal exhibit a consistent urban-rural distribution at the NUTS3 level.

Table 6: Intermediate outputs and FRI. Average values by Member States

Country	**Average Role of Agriculture**	**Average Natural Landscape**	**Average FRI**
Austria	0.333783332	0.185619018	0.560246872
Belgium	0.207783622	0.784305207	0.411411451
Bulgaria	0.921385068	0.332158479	0.960891485
Croatia	0.753237821	0.232765776	0.837718134
Cyprus	0.379144975	0.248743021	0.813084648
Czechia	0.435669787	0.419754907	0.771238453
Denmark	0.418634772	0.883027927	0.570057478
Estonia	0.610917619	0	0.659837701
Finland	0.766420335	0	0.90555121
France	0.348808209	0.4966101	0.571733124
Germany	0.100016989	0.594318668	0.210035742
Greece	0.799124914	0.126971612	0.873840291
Hungary	0.910233785	0.606986347	0.947365352
Ireland	0.372868689	0.941253865	0.672093899
Italy	0.53808157	0.401145374	0.721669228
Latvia	0.749335259	0.19965362	0.825338107
Lithuania	0.786436229	0.402045178	0.902025174
Luxembourg	0	0.442660627	0
Malta	0.392270031	0.704149602	0.624158883
Netherland	0.497678082	0.891939616	0.697502067
Poland	0.561609798	0.49092789	0.729459342
Portugal	0.622410745	0.142613368	0.801106293
Romania	0.840844991	0.488594173	0.928369843
Slovakia	0.638269188	0.292332471	0.895431604
Slovenia	0.512845501	0.087786514	0.755101984
Spain	0.71971321	0.160570363	0.830425894
Sweden	0.377249254	0.020929476	0.639971417
United Kingdom	0.172025095	0.852699951	0.266764576

Notes: table reports the average values for the two intermediate outputs, *Role of Agriculture* and *Natural Landscape* and for the final output, the FRI, for each Member State.

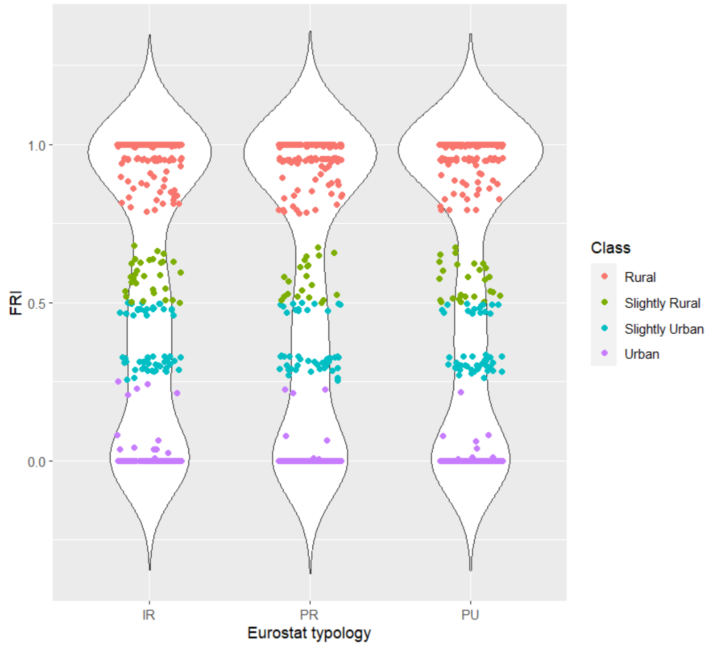
Figure 9: FRI distribution within each Member States



Notes: the boxplot represents the FRI distribution across the EU-28 Member States. It highlights the territorial heterogeneity within European countries.

In addition, also in this case the observed scenario deviates significantly from the initial expectations. What is noticeable is a uniform distribution of regions across the three Eurostat categories. Specifically, when examining the average FRI values for predominantly urban, predominantly rural, and intermediate regions, remarkably similar figures are observed: 0.56, 0.52, and 0.52 respectively. The analysis is summed up in the Figure 10 in the form of violin plot.

Figure 10: Distribution NUTS3 regions by FRI values throughout Eurostat categories



Notes: the graph is a violin plot which, using density curves, depicts distributions of NUTS-3 regions throughout the four Eurostat's rural-urban categories.

Finally, the robustness check concludes with performing a one-way ANOVA test which confirms that all classes are significantly different in terms of FRI as reported in the table below.

Table 7: Turkey DHS test results for FRI categories

Simultaneous Tests for General Linear Hypotheses Multiple Comparisons of Means: Tukey Contrasts Linear Hypotheses:	Estimate	Std. Error	t value	Pr(>|t|)
Slightly Rural - Rural == 0	-0. 394111	0. 006874	-57.34	<2e-16 ***
Slightly Urban - Rural == 0	-0. 608694	0. 005195	-117.18	<2e-16 ***
Urban - Rural == 0	-0. 959761	0. 004090	-234.67	<2e-16 ***
Slightly Urban - Slightly Rural == 0	-0. 214583	0. 007902	-27.16	<2e-16 ***
Urban - Slightly Rural == 0	-0. 565651	0. 007224	-78.30	<2e-16 ***
Urban - Slightly Urban == 0	-0. 351068	0. 005650	-62.14	<2e-16 ***
(Adjusted p values reported – single-step method)				

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

6. Conclusions

As Van der Ploeg et al. (2000) theorize, the concept of rurality and, in general, of rural development is a "disputed notion, both in practice, policy and theory". Still nowadays, the lack of a shared theoretical definition of what is rural persists in literature and this influences the originated taxonomies.

The aim of this paper is to provide a new multidimensional and continuous indicator to classify NUTS3 in EU-28 according to a degree of rurality. The paper tries to move forward in defining rural areas overcoming the traditional definitions based exclusively on population density criterion proposed by OECD (1994, 1996a, 2006) and Eurostat (2010). A multidimensional approach is more appropriate to describe the pronounced heterogeneity within European territory. Therefore, the Fuzzy Rurality Indicator is built upon six variables that capture three thematic areas: role of agriculture, demographic issue and landscape features. Results show the importance of rural areas throughout European continent. Taking into consideration FRI in terms of land area (km^2) and population, EU-28 appears largely a rural continent. More specifically, looking at FRI in relation to land area, rural regions cover the EU-28 territory for 72.6% of the total European Union land area. In addition, analysing FRI in terms of population, findings show that 66.6% of European inhabitants live in rural areas. According to FRI, the most rural countries are sited in Eastern countries (Hungary, Romania and Czechia); while the most urban ones are in the North of Europe (United Kingdom and Belgium). This first insight is at the basis of this study's motivation. Indeed, classifying correctly European areas has relevant policy and socio-economic implications and drives political choices (e.g., funds allocation). Findings contrast with existing taxonomies and suggest that a single parameter is not likely to be a good indicator in describing European complexity. By contrast, the FRI appears a good indicator because is comprehensible and adaptable. Furthermore, this classification stands out against the previous studies which mainly do not highlight great differences in comparison to the current taxonomies and contributes to enrich the literature on rurality indicators. The main limitation of this study lays in not considering a pure economic variable. Therefore, distinguishing between more economically developed and "lagging–behind" regions is not possible and should deepen in future works. Nevertheless, the FRI provides additional information and its use could foster development and growth in zones that need more help.

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Appendix

A.1 Rule blocks tables and FRI values

Table A1 and Table A2 illustrate rule blocks for the two intermediate outputs, role of agriculture and natural landscape, respectively. For both intermediate outputs, three input variables occur and show three qualitative categories (low, medium and high). Thus, 27 rules (3^3) are listed and five qualitative categories (very low, low, medium, high and very high) characterize each intermediate outputs for role of agriculture and natural landscape, respectively. Table A3 define rule blocks for FRI. In this case, the two intermediate outputs are adopted as inputs and are described by five qualitative categories. Therefore, 25 rules (5^2) are listed. Finally, seven qualitative categories (very low, low, medium-low, medium, medium-high, high, very high) identify FRI.

Table A1: Rule block for role of agriculture intermediate indicator

IF			THEN
Agricultural GVA	Employment in agriculture	Agricultural areas	Role of agriculture indicator
Low	Low	Low	Very Low
Low	Low	Medium	Low
Low	Low	High	Low
Low	Medium	Low	Low
Low	Medium	Medium	Low
Low	Medium	High	Medium
Low	High	Low	Low
Low	High	Medium	Medium
Low	High	High	High
Medium	Low	Low	Low
Medium	Low	Medium	Low
Medium	Low	High	Medium
Medium	Medium	Low	Low
Medium	Medium	Medium	Medium
Medium	Medium	High	High
Medium	High	Low	Medium
Medium	High	Medium	High
Medium	High	High	High
High	Low	Low	Low
High	Low	Medium	Medium
High	Low	High	High
High	Medium	Low	Medium
High	Medium	Medium	High
High	Medium	High	High
High	High	Low	High
High	High	Medium	High
High	High	High	Very high

Notes: table reports the rule blocks for the Role of agriculture intermediate indicator. The three input variables assume three qualitative categories (low, medium and high). Then, 27 rules (3^3) are defined and the final output is characterized by five qualitative categories (very low, low, medium, high and very high).

Table A2: Rule block for natural landscape intermediate indicator

IF			THEN
Artificial areas	Forests	Density	Natural landscape indicator
Low	Low	Low	High
Low	Low	Medium	Medium
Low	Low	High	Low
Low	Medium	Low	High
Low	Medium	Medium	High
Low	Medium	High	Medium
Low	High	Low	Very high
Low	High	Medium	High
Low	High	High	High
Medium	Low	Low	Medium
Medium	Low	Medium	Low
Medium	Low	High	Low
Medium	Medium	Low	High
Medium	Medium	Medium	Medium
Medium	Medium	High	Low
Medium	High	Low	High
Medium	High	Medium	High
Medium	High	High	Medium
High	Low	Low	Low
High	Low	Medium	Low
High	Low	High	Very low
High	Medium	Low	Medium
High	Medium	Medium	Low
High	Medium	High	Low
High	High	Low	High
High	High	Medium	Medium
High	High	High	Low

Notes: table reports the rule blocks for the Natural landscape intermediate indicator. The three input variables assume three qualitative categories (low, medium and high). Then, 27 rules (3^3) are defined and the final output is characterized by five qualitative categories (very low, low, medium, high and very high).

Table A3: Rule block for FRI

IF			THEN
Artificial areas	Forests	Density	Natural landscape indicator
Low	Low	Low	High
Low	Low	Medium	Medium
Low	Low	High	Low
Low	Medium	Low	High
Low	Medium	Medium	High
Low	Medium	High	Medium
Low	High	Low	Very high
Low	High	Medium	High
Low	High	High	High
Medium	Low	Low	Medium
Medium	Low	Medium	Low
Medium	Low	High	Low
Medium	Medium	Low	High
Medium	Medium	Medium	Medium
Medium	Medium	High	Low
Medium	High	Low	High
Medium	High	Medium	High
Medium	High	High	Medium
High	Low	Low	Low
High	Low	Medium	Low
High	Low	High	Very low
High	Medium	Low	Medium
High	Medium	Medium	Low
High	Medium	High	Low
High	High	Low	High
High	High	Medium	Medium
High	High	High	Low

Notes: the table defines rule blocks for the final output FRI. In this case, the two intermediate outputs are adopted as inputs and are described by five qualitative categories. Therefore, 25 rules (5^2) are listed. Finally, seven qualitative categories (very low, low, medium-low, medium, medium-high, high, very high) identify FRI.

FRI values for each NUTS3 regions in EU-28 are listed below in Table A4.

Table A4: FRI values for each NUTS-3 region

Geo	FRI	Class	Geo	FRI	Class	Geo	FRI	Class
AT111	0.03	Urban	ES513	1	Rural	PL219	0.34	Slightly Urban
AT112	0.65	Slightly Rural	ES514	1	Rural	PL21A	0.28	Slightly Urban
AT113	0.17	Urban	ES521	1	Rural	PL224	0.82	Rural
AT121	1	Rural	ES522	1	Rural	PL225	0.19	Urban
AT122	0.41	Slightly Urban	ES523	1	Rural	PL227	0.18	Urban
AT123	0.19	Urban	ES531	0	Urban	PL228	0.17	Urban
AT124	1	Rural	ES532	0.33	Slightly Urban	PL229	0	Urban
AT125	0.79	Rural	ES533	0	Urban	PL22A	0	Urban
AT126	0.84	Rural	ES611	1	Rural	PL22B	0.26	Slightly Urban
AT127	0.18	Urban	ES612	1	Rural	PL22C	0.01	Urban
AT130	0	Urban	ES613	1	Rural	PL411	1	Rural
AT211	0.18	Urban	ES614	1	Rural	PL414	1	Rural
AT212	0.27	Slightly Urban	ES615	1	Rural	PL415	0	Urban
AT213	0.38	Slightly Urban	ES616	1	Rural	PL416	1	Rural
AT221	0.18	Urban	ES617	1	Rural	PL417	1	Rural
AT222	0.19	Urban	ES618	1	Rural	PL418	1	Rural
AT223	0.28	Slightly Urban	ES620	1	Rural	PL424	0	Urban
AT224	1	Rural	FI193	1	Rural	PL426	0.39	Slightly Urban
AT225	0.46	Slightly Urban	FI194	1	Rural	PL427	1	Rural
AT226	0.27	Slightly Urban	FI195	0.87	Rural	PL428	0.97	Rural
AT311	1	Rural	FI196	0.86	Rural	PL431	0.79	Rural
AT312	0.35	Slightly Urban	FI197	1	Rural	PL432	0.98	Rural
AT313	0.86	Rural	FI1B1	0.87	Rural	PL514	0	Urban
AT314	0.35	Slightly Urban	FI1C1	1	Rural	PL515	0.81	Rural
AT315	0.46	Slightly Urban	FI1C2	0.37	Slightly Urban	PL516	0.4	Slightly Urban
AT321	0	Urban	FI1C3	0.83	Rural	PL517	0.71	Slightly Rural
AT322	0.19	Urban	FI1C4	0.35	Slightly Urban	PL518	1	Rural
AT323	0.26	Slightly Urban	FI1C5	0.45	Slightly Urban	PL523	0.98	Rural
AT331	0	Urban	FI1D1	1	Rural	PL524	0.97	Rural
AT332	0.03	Urban	FI1D2	1	Rural	PL613	0.35	Slightly Urban
AT333	0	Urban	FI1D3	0.98	Rural	PL616	1	Rural
AT334	0	Urban	FI1D5	0.18	Urban	PL617	0.99	Rural
AT335	0.28	Slightly Urban	FI1D7	0.86	Rural	PL618	0.67	Slightly Rural
AT341	0	Urban	FI1D8	0.27	Slightly Urban	PL619	0.98	Rural
AT342	0	Urban	FI1D9	1	Rural	PL621	1	Rural
BE100	0	Urban	FI200	0	Urban	PL622	1	Rural

BE211	0.37	Slightly Urban	FR101	0	Urban	PL623	0.86	Rural
BE212	0.26	Slightly Urban	FR102	1	Rural	PL633	0	Urban
BE213	1	Rural	FR103	0.26	Slightly Urban	PL634	0.76	Rural
BE221	0.27	Slightly Urban	FR104	0.18	Urban	PL636	0.72	Slightly Rural
BE222	0.19	Urban	FR105	0	Urban	PL637	0.29	Slightly Urban
BE223	0.27	Slightly Urban	FR106	0	Urban	PL638	0.86	Rural
BE231	0	Urban	FR107	0	Urban	PL711	0	Urban
BE232	0.18	Urban	FR108	0.18	Urban	PL712	0.81	Rural
BE233	0.18	Urban	FRB01	1	Rural	PL713	1	Rural
BE234	0.86	Rural	FRB02	1	Rural	PL714	1	Rural
BE235	0	Urban	FRB03	0.87	Rural	PL715	1	Rural
BE236	0.18	Urban	FRB04	1	Rural	PL721	0.87	Rural
BE241	0.15	Urban	FRB05	1	Rural	PL722	1	Rural
BE242	0.41	Slightly Urban	FRB06	1	Rural	PL811	0.99	Rural
BE251	0.35	Slightly Urban	FRC11	1	Rural	PL812	1	Rural
BE252	0.18	Urban	FRC12	1	Rural	PL814	0.87	Rural
BE253	0.28	Slightly Urban	FRC13	1	Rural	PL815	0.98	Rural
BE254	0.17	Urban	FRC14	1	Rural	PL821	0.31	Slightly Urban
BE255	0.03	Urban	FRC21	0.98	Rural	PL822	0.38	Slightly Urban
BE256	0.29	Slightly Urban	FRC22	0.86	Rural	PL823	0.33	Slightly Urban
BE257	0.64	Slightly Rural	FRC23	0.86	Rural	PL824	0.37	Slightly Urban
BE258	0	Urban	FRC24	0	Urban	PL841	0.96	Rural
BE310	0.18	Urban	FRD11	1	Rural	PL842	1	Rural
BE321	0	Urban	FRD12	1	Rural	PL843	0.99	Rural
BE322	0	Urban	FRD13	0.98	Rural	PL911	0	Urban
BE323	0	Urban	FRD21	0.99	Rural	PL912	1	Rural
BE324	0	Urban	FRD22	1	Rural	PL913	0.99	Rural
BE325	0	Urban	FRE11	1	Rural	PL921	1	Rural
BE326	0	Urban	FRE12	1	Rural	PL922	1	Rural
BE327	0.16	Urban	FRE21	1	Rural	PL923	1	Rural
BE331	0	Urban	FRE22	1	Rural	PL924	1	Rural
BE332	0	Urban	FRE23	1	Rural	PL925	1	Rural
BE334	0	Urban	FRF11	1	Rural	PL926	1	Rural
BE335	0.16	Urban	FRF12	1	Rural	PT111	0.18	Urban
BE336	0	Urban	FRF21	1	Rural	PT112	0.27	Slightly Urban
BE341	0	Urban	FRF22	1	Rural	PT119	0.18	Urban
BE342	0	Urban	FRF23	1	Rural	PT11A	1	Rural
BE343	0	Urban	FRF24	0.87	Rural	PT11B	0.18	Urban

BE344	0.02	Urban	FRF31	0.86	Rural	PT11C	0.18	Urban
BE345	0	Urban	FRF32	1	Rural	PT11D	0.86	Rural
BE351	0.18	Urban	FRF33	0.98	Rural	PT11E	0.27	Slightly Urban
BE352	0.15	Urban	FRF34	0.98	Rural	PT150	1	Rural
BE353	0	Urban	FRG01	1	Rural	PT16B	1	Rural
BG311	0.27	Slightly Urban	FRG02	1	Rural	PT16D	0.64	Slightly Rural
BG312	0.38	Slightly Urban	FRG03	1	Rural	PT16E	0.97	Rural
BG313	0.4	Slightly Urban	FRG04	1	Rural	PT16F	0.63	Slightly Rural
BG314	0.76	Rural	FRG05	1	Rural	PT16G	0.64	Slightly Rural
BG315	0.26	Slightly Urban	FRH01	1	Rural	PT16H	0.18	Urban
BG321	0.31	Slightly Urban	FRH02	1	Rural	PT16I	0.64	Slightly Rural
BG322	0	Urban	FRH03	1	Rural	PT16J	0.28	Slightly Urban
BG323	0.37	Slightly Urban	FRH04	1	Rural	PT170	1	Rural
BG324	0.38	Slightly Urban	FRI11	1	Rural	PT181	0.87	Rural
BG325	0.43	Slightly Urban	FRI12	1	Rural	PT184	0.86	Rural
BG331	0.28	Slightly Urban	FRI13	1	Rural	PT185	1	Rural
BG332	0.85	Rural	FRI14	1	Rural	PT186	0.81	Rural
BG333	0.38	Slightly Urban	FRI15	1	Rural	PT187	1	Rural
BG334	0.27	Slightly Urban	FRI21	0.87	Rural	RO111	1	Rural
BG341	0.86	Rural	FRI22	0.73	Slightly Rural	RO112	1	Rural
BG342	0.28	Slightly Urban	FRI23	0.86	Rural	RO113	1	Rural
BG343	0.26	Slightly Urban	FRI31	1	Rural	RO114	1	Rural
BG344	0.73	Slightly Rural	FRI32	1	Rural	RO115	1	Rural
BG411	0.18	Urban	FRI33	1	Rural	RO116	0.87	Rural
BG412	0.39	Slightly Urban	FRI34	1	Rural	RO121	1	Rural
BG413	0.99	Rural	FRJ11	1	Rural	RO122	1	Rural
BG414	0.17	Urban	FRJ12	1	Rural	RO123	1	Rural
BG415	0.39	Slightly Urban	FRJ13	1	Rural	RO124	1	Rural
BG421	1	Rural	FRJ14	0.18	Urban	RO125	1	Rural
BG422	0.79	Rural	FRJ15	0.87	Rural	RO126	0.99	Rural
BG423	0.86	Rural	FRJ21	0.17	Urban	RO211	1	Rural
BG424	0.27	Slightly Urban	FRJ22	0.97	Rural	RO212	1	Rural
BG425	0.86	Rural	FRJ23	0.74	Slightly Rural	RO213	1	Rural
CY000	1	Rural	FRJ24	1	Rural	RO214	1	Rural
CZ010	0.78	Rural	FRJ25	0.4	Slightly Urban	RO215	1	Rural
CZ020	1	Rural	FRJ26	0.18	Urban	RO216	0.98	Rural
CZ031	1	Rural	FRJ27	0.86	Rural	RO221	1	Rural
CZ032	1	Rural	FRJ28	0.83	Rural	RO222	1	Rural

CZ041	0.31	Slightly Urban	FRK11	0.98	Rural	RO223	1	Rural
CZ042	0.86	Rural	FRK12	0.85	Rural	RO224	1	Rural
CZ051	0.27	Slightly Urban	FRK13	0.82	Rural	RO225	0.4	Slightly Urban
CZ052	1	Rural	FRK14	1	Rural	RO226	1	Rural
CZ053	1	Rural	FRK21	0.87	Rural	RO311	1	Rural
CZ063	1	Rural	FRK22	0.36	Slightly Urban	RO312	0.86	Rural
CZ064	1	Rural	FRK23	1	Rural	RO313	1	Rural
CZ071	1	Rural	FRK24	0.87	Rural	RO314	0.45	Slightly Urban
CZ072	0.96	Rural	FRK25	0.73	Slightly Rural	RO315	0.76	Rural
CZ080	1	Rural	FRK26	1	Rural	RO316	1	Rural
DE11	1	Rural	FRK27	0.26	Slightly Urban	RO317	0.96	Rural
DE12	0.4	Slightly Urban	FRK28	0.39	Slightly Urban	RO321	0	Urban
DE13	1	Rural	FRL01	0.18	Urban	RO322	0.39	Slightly Urban
DE14	1	Rural	FRL02	0.13	Urban	RO411	1	Rural
DE21	1	Rural	FRL03	0	Urban	RO412	0.97	Rural
DE22	1	Rural	FRL04	1	Rural	RO413	0.63	Slightly Rural
DE23	1	Rural	FRL05	1	Rural	RO414	1	Rural
DE24	1	Rural	FRL06	1	Rural	RO415	1	Rural
DE25	1	Rural	FRM01	0	Urban	RO421	1	Rural
DE26	1	Rural	FRM02	0.18	Urban	RO422	1	Rural
DE27	1	Rural	HR031	0.18	Urban	RO423	0.97	Rural
DE40	1	Rural	HR032	0.18	Urban	RO424	1	Rural
DE50	0	Urban	HR033	0.29	Slightly Urban	SE110	0.33	Slightly Urban
DE71	0.78	Rural	HR034	0	Urban	SE121	0.45	Slightly Urban
DE72	0.86	Rural	HR035	0.18	Urban	SE122	0.3	Slightly Urban
DE73	1	Rural	HR036	0.19	Urban	SE123	0.86	Rural
DE80	1	Rural	HR037	0.17	Urban	SE124	0.44	Slightly Urban
DE91	1	Rural	HR041	0	Urban	SE125	0.26	Slightly Urban
DE92	1	Rural	HR042	0.86	Rural	SE211	1	Rural
DE93	1	Rural	HR043	0.16	Urban	SE212	0.86	Rural
DE94	1	Rural	HR044	0.3	Slightly Urban	SE213	0.99	Rural
DEA1	0.98	Rural	HR045	0.84	Rural	SE214	0.05	Urban
DEA2	0.86	Rural	HR046	0.35	Slightly Urban	SE221	0.27	Slightly Urban
DEA3	1	Rural	HR047	0.86	Rural	SE224	1	Rural
DEA4	1	Rural	HR048	0.65	Slightly Rural	SE231	0.74	Slightly Rural
DEA5	0.97	Rural	HR049	0.27	Slightly Urban	SE232	1	Rural
DEB1	1	Rural	HR04A	0.38	Slightly Urban	SE311	0.87	Rural
DEB2	0.87	Rural	HR04B	1	Rural	SE312	0.97	Rural

DEB3	1	Rural	HR04C	0.99	Rural	SE313	0.98	Rural
DEC0	0	Urban	HR04D	0.18	Urban	SE321	0.87	Rural
DED2	0.97	Rural	HR04E	0.29	Slightly Urban	SE322	0.87	Rural
DED4	1	Rural	HU110	0.29	Slightly Urban	SE331	1	Rural
DED5	0.64	Slightly Rural	HU120	1	Rural	SE332	0.86	Rural
DEE0	1	Rural	HU211	1	Rural	SI031	0.27	Slightly Urban
DEF0	1	Rural	HU212	0.86	Rural	SI032	0.39	Slightly Urban
DEG0	1	Rural	HU213	0.87	Rural	SI033	0	Urban
DE111	0	Urban	HU221	1	Rural	SI034	0.29	Slightly Urban
DE112	0	Urban	HU222	1	Rural	SI035	0	Urban
DE113	0	Urban	HU223	0.86	Rural	SI036	0.16	Urban
DE114	0	Urban	HU231	0.98	Rural	SI037	0.28	Slightly Urban
DE115	0.18	Urban	HU232	1	Rural	SI038	0.14	Urban
DE116	0.05	Urban	HU233	0.97	Rural	SI041	0.28	Slightly Urban
DE121	0	Urban	HU311	0.99	Rural	SI042	0.18	Urban
DE122	0	Urban	HU312	0.74	Slightly Rural	SI043	0.18	Urban
DE123	0	Urban	HU313	0.17	Urban	SI044	0	Urban
DE124	0	Urban	HU321	1	Rural	SK010	0.99	Rural
DE125	0	Urban	HU322	1	Rural	SK021	1	Rural
DE126	0	Urban	HU323	1	Rural	SK022	0.99	Rural
DE128	0.17	Urban	HU331	1	Rural	SK023	1	Rural
DE212	0	Urban	HU332	1	Rural	SK031	0.98	Rural
DE21H	0	Urban	HU333	1	Rural	SK032	1	Rural
DE252	0	Urban	IE041	0.96	Rural	SK041	1	Rural
DE253	0	Urban	IE042	0.38	Slightly Urban	SK042	1	Rural
DE254	0	Urban	IE051	1	Rural	UKC11	0	Urban
DE255	0	Urban	IE052	1	Rural	UKC12	0	Urban
DE257	0	Urban	IE053	1	Rural	UKC13	0	Urban
DE258	0	Urban	IE061	0.18	Urban	UKC14	0.18	Urban
DE261	0	Urban	IE062	0.98	Rural	UKC21	0.78	Rural
DE264	0	Urban	IE063	0.26	Slightly Urban	UKC22	0	Urban
DE271	0	Urban	ITC11	1	Rural	UKC23	0	Urban
DE276	0.18	Urban	ITC12	0.79	Rural	UKD11	0.18	Urban
DE300	0	Urban	ITC13	0	Urban	UKD12	0.76	Rural
DE501	0	Urban	ITC14	0	Urban	UKD33	0	Urban
DE600	0.18	Urban	ITC15	0.43	Slightly Urban	UKD34	0	Urban
DE711	0	Urban	ITC16	1	Rural	UKD35	0	Urban
DE712	0	Urban	ITC17	0.74	Slightly Rural	UKD36	0	Urban

DE713	0	Urban	ITC18	0.99	Rural	UKD37	0	Urban
DE714	0	Urban	ITC20	0.18	Urban	UKD41	0	Urban
DE715	0	Urban	ITC31	1	Rural	UKD42	0	Urban
DE716	0.13	Urban	ITC32	0.86	Rural	UKD44	0	Urban
DE717	0	Urban	ITC33	0.19	Urban	UKD45	0	Urban
DE718	0	Urban	ITC34	0.17	Urban	UKD46	0	Urban
DE71A	0	Urban	ITC41	0.17	Urban	UKD47	0.18	Urban
DE71C	0	Urban	ITC42	0.19	Urban	UKD61	0	Urban
DE929	0.28	Slightly Urban	ITC43	0	Urban	UKD62	0.27	Slightly Urban
DE941	0	Urban	ITC44	0.19	Urban	UKD63	0	Urban
DEA11	0	Urban	ITC46	1	Rural	UKD71	0	Urban
DEA12	0	Urban	ITC47	1	Rural	UKD72	0	Urban
DEA13	0	Urban	ITC48	1	Rural	UKD73	0	Urban
DEA14	0	Urban	ITC49	0.87	Rural	UKD74	0	Urban
DEA15	0	Urban	ITC4A	1	Rural	UKE11	0	Urban
DEA16	0	Urban	ITC4B	1	Rural	UKE12	0.96	Rural
DEA17	0	Urban	ITC4C	0.87	Rural	UKE13	0.26	Slightly Urban
DEA18	0	Urban	ITC4D	0.02	Urban	UKE21	0	Urban
DEA19	0	Urban	ITF11	0.79	Rural	UKE22	1	Rural
DEA1A	0	Urban	ITF12	0.76	Rural	UKE31	0.13	Urban
DEA1C	0	Urban	ITF13	0.36	Slightly Urban	UKE32	0	Urban
DEA1D	0.13	Urban	ITF14	0.86	Rural	UKE41	0	Urban
DEA1E	0.18	Urban	ITF21	0.18	Urban	UKE42	0	Urban
DEA1F	0.18	Urban	ITF22	0.86	Rural	UKE44	0	Urban
DEA22	0	Urban	ITF31	1	Rural	UKE45	0	Urban
DEA23	0	Urban	ITF32	0.98	Rural	UKF11	0	Urban
DEA24	0	Urban	ITF33	1	Rural	UKF12	0	Urban
DEA27	0.01	Urban	ITF34	0.99	Rural	UKF13	0.18	Urban
DEA2B	0	Urban	ITF35	1	Rural	UKF14	0	Urban
DEA2C	0.18	Urban	ITF43	1	Rural	UKF15	0.26	Slightly Urban
DEA2D	0	Urban	ITF44	0.87	Rural	UKF16	0	Urban
DEA31	0	Urban	ITF45	0.98	Rural	UKF21	0	Urban
DEA32	0	Urban	ITF46	1	Rural	UKF22	0.34	Slightly Urban
DEA33	0	Urban	ITF47	1	Rural	UKF24	0.17	Urban
DEA35	0.3	Slightly Urban	ITF48	0.98	Rural	UKF25	0	Urban
DEA36	0	Urban	ITF51	1	Rural	UKF30	1	Rural
DEA41	0	Urban	ITF52	1	Rural	UKG11	0.99	Rural
DEA42	0.18	Urban	ITF61	1	Rural	UKG12	0.39	Slightly Urban

DEA43	0	Urban	ITF62	0.74	Slightly Rural	UKG13	0.19	Urban
DEA51	0	Urban	ITF63	1	Rural	UKG21	0	Urban
DEA52	0	Urban	ITF64	0.44	Slightly Urban	UKG22	0.87	Rural
DEA53	0	Urban	ITF65	1	Rural	UKG23	0	Urban
DEA54	0	Urban	ITG11	1	Rural	UKG24	0.3	Slightly Urban
DEA55	0	Urban	ITG12	1	Rural	UKG31	0	Urban
DEA56	0	Urban	ITG13	0.99	Rural	UKG32	0	Urban
DEA58	0	Urban	ITG14	1	Rural	UKG33	0	Urban
DEA5C	0	Urban	ITG15	0.8	Rural	UKG36	0	Urban
DEB31	0	Urban	ITG16	0.85	Rural	UKG37	0	Urban
DEB33	0	Urban	ITG17	1	Rural	UKG38	0	Urban
DEB34	0	Urban	ITG18	1	Rural	UKG39	0	Urban
DEB35	0	Urban	ITG19	1	Rural	UKH11	0	Urban
DEB38	0	Urban	ITG25	1	Rural	UKH12	0.87	Rural
DEB39	0	Urban	ITG26	0.83	Rural	UKH14	1	Rural
DEB3E	0.15	Urban	ITG27	1	Rural	UKH15	0.29	Slightly Urban
DEB3I	0.27	Slightly Urban	ITG28	1	Rural	UKH16	1	Rural
DEC01	0	Urban	ITG29	0.29	Slightly Urban	UKH17	0.98	Rural
DEC04	0	Urban	ITG2A	0.04	Urban	UKH21	0	Urban
DEC05	0	Urban	ITG2B	0.26	Slightly Urban	UKH23	0	Urban
DED21	0	Urban	ITG2C	0.19	Urban	UKH24	0	Urban
DED2F	0.18	Urban	ITH10	1	Rural	UKH25	0	Urban
DED51	0	Urban	ITH20	1	Rural	UKH31	0	Urban
DED52	0.26	Slightly Urban	ITH31	1	Rural	UKH32	0	Urban
DEF02	0	Urban	ITH32	1	Rural	UKH34	0.17	Urban
DEF09	0.19	Urban	ITH33	0.18	Urban	UKH35	0	Urban
DEF0A	0.17	Urban	ITH34	1	Rural	UKH36	0	Urban
DK011	0	Urban	ITH35	1	Rural	UKH37	0	Urban
DK012	0	Urban	ITH36	1	Rural	UKI31	0	Urban
DK013	0	Urban	ITH37	1	Rural	UKI32	0	Urban
DK014	0	Urban	ITH41	0.86	Rural	UKI33	0	Urban
DK021	0	Urban	ITH42	1	Rural	UKI34	0	Urban
DK022	1	Rural	ITH43	0.17	Urban	UKI41	0	Urban
DK031	0.99	Rural	ITH44	0.03	Urban	UKI42	0	Urban
DK032	1	Rural	ITH51	1	Rural	UKI43	0	Urban
DK041	1	Rural	ITH52	1	Rural	UKI44	0	Urban
DK042	0.99	Rural	ITH53	1	Rural	UKI45	0	Urban
DK050	1	Rural	ITH54	1	Rural	UKI51	0	Urban

EE001	0.36	Slightly Urban	ITH55	1	Rural	UKI52	0	Urban
EE004	0.43	Slightly Urban	ITH56	1	Rural	UKI53	0	Urban
EE006	0.76	Rural	ITH57	1	Rural	UKI54	0	Urban
EE007	0	Urban	ITH58	1	Rural	UKI61	0	Urban
EE008	1	Rural	ITH59	0.4	Slightly Urban	UKI62	0	Urban
EL301	0	Urban	ITI11	0.12	Urban	UKI63	0	Urban
EL302	0	Urban	ITI12	0.28	Slightly Urban	UKI71	0	Urban
EL303	0.03	Urban	ITI13	1	Rural	UKI72	0	Urban
EL304	0	Urban	ITI14	0.97	Rural	UKI73	0	Urban
EL305	0.96	Rural	ITI15	0	Urban	UKI74	0	Urban
EL306	0.18	Urban	ITI16	0.64	Slightly Rural	UKI75	0	Urban
EL307	0.18	Urban	ITI17	0.98	Rural	UKJ11	0	Urban
EL411	0.19	Urban	ITI18	0.86	Rural	UKJ12	0	Urban
EL412	0	Urban	ITI19	1	Rural	UKJ13	0.17	Urban
EL413	0	Urban	ITI1A	1	Rural	UKJ14	0.35	Slightly Urban
EL421	0.27	Slightly Urban	ITI21	1	Rural	UKJ21	0	Urban
EL422	0.27	Slightly Urban	ITI22	0.19	Urban	UKJ22	0.18	Urban
EL431	1	Rural	ITI31	0.44	Slightly Urban	UKJ25	0.01	Urban
EL432	0.77	Rural	ITI32	0.87	Rural	UKJ26	0	Urban
EL433	0.28	Slightly Urban	ITI33	0.77	Rural	UKJ27	0.18	Urban
EL434	0.86	Rural	ITI34	0.43	Slightly Urban	UKJ28	0	Urban
EL511	0.66	Slightly Rural	ITI35	0.18	Urban	UKJ31	0	Urban
EL512	0.27	Slightly Urban	ITI41	1	Rural	UKJ32	0	Urban
EL513	0.32	Slightly Urban	ITI42	0.38	Slightly Urban	UKJ34	0	Urban
EL514	0.41	Slightly Urban	ITI43	1	Rural	UKJ35	0	Urban
EL515	0.73	Slightly Rural	ITI44	1	Rural	UKJ36	0.29	Slightly Urban
EL521	1	Rural	ITI45	0.83	Rural	UKJ37	0	Urban
EL522	1	Rural	LT011	0.98	Rural	UKJ41	0	Urban
EL523	0.42	Slightly Urban	LT021	0.19	Urban	UKJ43	0.18	Urban
EL524	1	Rural	LT022	1	Rural	UKJ44	0.19	Urban
EL525	0.34	Slightly Urban	LT023	0.45	Slightly Urban	UKJ45	0.19	Urban
EL526	1	Rural	LT024	0.86	Rural	UKJ46	0.18	Urban
EL527	0.29	Slightly Urban	LT025	0.97	Rural	UKK11	0	Urban
EL531	0.63	Slightly Rural	LT026	1	Rural	UKK12	0.17	Urban
EL532	0.18	Urban	LT027	0.27	Slightly Urban	UKK13	0.41	Slightly Urban
EL533	0.27	Slightly Urban	LT028	0.19	Urban	UKK14	0	Urban
EL541	0.86	Rural	LT029	0.19	Urban	UKK15	0.37	Slightly Urban
EL542	0.17	Urban	LU000	0.43	Slightly Urban	UKK21	0	Urban

EL543	0.27	Slightly Urban	LV003	0.87	Rural	UKK22	0.31	Slightly Urban
EL611	0.99	Rural	LV005	0.7	Slightly Rural	UKK23	0.86	Rural
EL612	1	Rural	LV006	0.27	Slightly Urban	UKK30	0.98	Rural
EL613	0.42	Slightly Urban	LV007	0.43	Slightly Urban	UKK41	0	Urban
EL621	0	Urban	LV008	1	Rural	UKK42	0	Urban
EL622	0.17	Urban	LV009	0.98	Rural	UKK43	1	Rural
EL623	0.15	Urban	MT001	0.38	Slightly Urban	UKL11	0	Urban
EL624	0	Urban	MT002	0	Urban	UKL12	0	Urban
EL631	1	Rural	NL111	0.43	Slightly Urban	UKL13	0	Urban
EL632	1	Rural	NL112	0	Urban	UKL14	0.31	Slightly Urban
EL633	1	Rural	NL113	0.86	Rural	UKL15	0	Urban
EL641	1	Rural	NL124	0.98	Rural	UKL16	0	Urban
EL642	0.87	Rural	NL125	0.18	Urban	UKL17	0	Urban
EL643	0	Urban	NL126	0.33	Slightly Urban	UKL18	0	Urban
EL644	1	Rural	NL131	0.37	Slightly Urban	UKL21	0	Urban
EL645	0	Urban	NL132	0.99	Rural	UKL22	0	Urban
EL651	1	Rural	NL133	0.18	Urban	UKL23	0	Urban
EL652	0.61	Slightly Rural	NL211	0.98	Rural	UKL24	0.18	Urban
EL653	1	Rural	NL212	0.19	Urban	UKM50	1	Rural
ES111	1	Rural	NL213	1	Rural	UKM61	0.18	Urban
ES112	1	Rural	NL221	1	Rural	UKM62	0.18	Urban
ES113	1	Rural	NL224	1	Rural	UKM63	0.26	Slightly Urban
ES114	1	Rural	NL225	1	Rural	UKM64	0	Urban
ES120	1	Rural	NL226	0.96	Rural	UKM65	0	Urban
ES130	1	Rural	NL230	1	Rural	UKM66	0.18	Urban
ES211	0.86	Rural	NL310	0.99	Rural	UKM71	0.99	Rural
ES212	0.86	Rural	NL321	1	Rural	UKM72	0.33	Slightly Urban
ES213	0.86	Rural	NL323	0	Urban	UKM73	0.19	Urban
ES220	1	Rural	NL324	0	Urban	UKM75	0.19	Urban
ES230	1	Rural	NL325	0	Urban	UKM76	0	Urban
ES241	1	Rural	NL327	0	Urban	UKM77	0.12	Urban
ES242	0.87	Rural	NL328	0.26	Slightly Urban	UKM78	0.26	Slightly Urban
ES243	1	Rural	NL329	1	Rural	UKM81	0	Urban
ES300	0.87	Rural	NL332	1	Rural	UKM82	0	Urban
ES411	0.85	Rural	NL333	1	Rural	UKM83	0	Urban
ES412	1	Rural	NL337	0.98	Rural	UKM84	0	Urban
ES413	1	Rural	NL33A	0.18	Urban	UKM91	0.7	Slightly Rural
ES414	1	Rural	NL33B	1	Rural	UKM92	0.18	Urban

ES415	1	Rural	NL33C	1	Rural	UKM93	1	Rural
ES416	1	Rural	NL341	0.38	Slightly Urban	UKM94	0	Urban
ES417	0.97	Rural	NL342	1	Rural	UKM95	0.18	Urban
ES418	1	Rural	NL411	1	Rural	UKN06	0	Urban
ES419	1	Rural	NL412	1	Rural	UKN07	0	Urban
ES421	1	Rural	NL413	1	Rural	UKN08	0.86	Rural
ES422	1	Rural	NL414	1	Rural	UKN09	0.15	Urban
ES423	1	Rural	NL421	1	Rural	UKN10	0	Urban
ES424	0.77	Rural	NL422	0.87	Rural	UKN11	0	Urban
ES425	1	Rural	NL423	0.18	Urban	UKN12	0.18	Urban
ES431	1	Rural	PL213	0	Urban	UKN13	0	Urban
ES432	1	Rural	PL214	1	Rural	UKN14	0	Urban
ES511	1	Rural	PL217	0.8	Rural	UKN15	0	Urban
ES512	1	Rural	PL218	0.78	Rural	UKN16	0.38	Slightly Urban

A.2 Rural-urban typology by Eurostat: in detail description

The rural-urban typology statistics adopted by Eurostat and used to classify NUTS-3 regions within EU-27 is based on a three-step approach. The first step is defining rural areas, the second one consists of classifying regions according to the share of population in rural areas and, finally, the presence of a city is taken into consideration.

To begin, the initial task involves identifying populations residing in rural areas. In this context, "rural areas" encompass all locations outside urban clusters. These "urban clusters" are comprised of contiguous grid cells measuring 1 km², with a minimum density of 300 inhabitants per km² and a population threshold of at least 5,000 individuals. This process leads to the classification of regions.

Secondly, the classification of NUTS 3 regions takes place, determined by the proportion of their population residing in rural areas. The categorization is as follows:

- Regions are labelled as "*Predominantly rural*" when the share of the population living in rural areas exceeds 50.

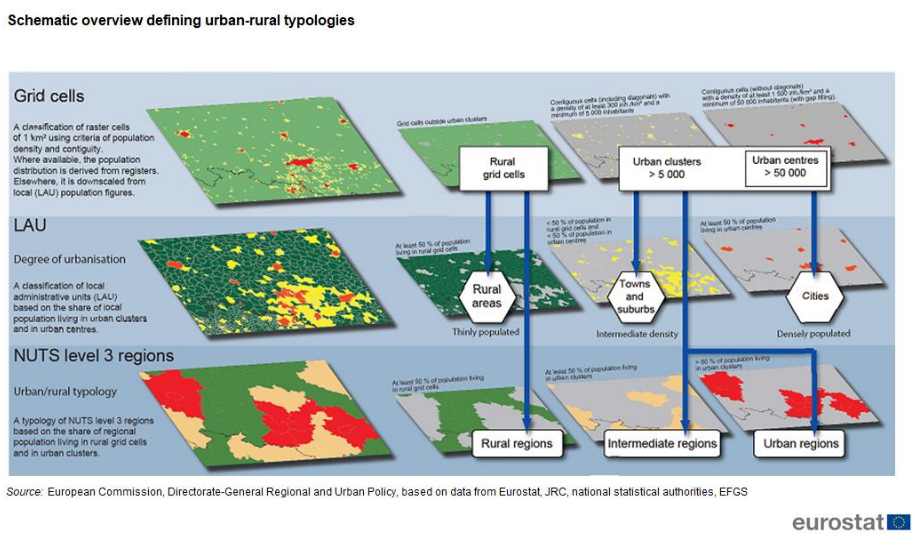
- If the share of the population living in rural areas falls between 20 and 50, the regions are classified as "*Intermediate*."
- "*Predominantly urban*" is assigned to regions where the share of the population living in rural areas is below 20.

To address the bias introduced by exceptionally small NUTS 3 regions, a solution is implemented wherein regions with an area smaller than 500 km² are merged with one or more adjacent neighbours for classification purposes. This consolidation helps mitigate the distortion caused by the diminutive size of such regions.

In the last step, the evaluation considers the size of urban centres within the region. If a predominantly rural region encompasses an urban centre with a population exceeding 200,000, constituting at least 25% of the overall regional population, it transitions to an intermediate classification. Likewise, an intermediate region qualifies as predominantly urban when it encompasses an urban centre with a population surpassing 500,000, accounting for at least 25% of the total regional population.

Below, a graphical representation of the abovementioned methodology is presented.

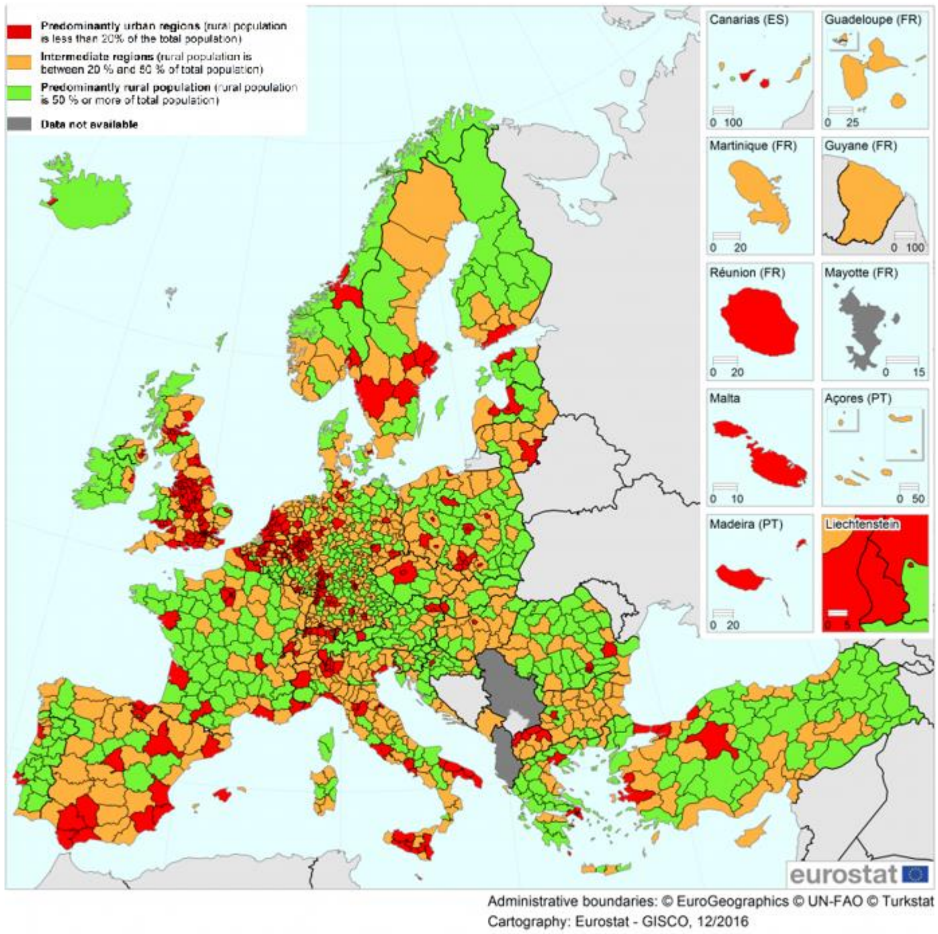
Figure A1: Schematic overview defining urban-rural typologies



For this work's purposes, it has been decided to adopt the type of classification that takes into consideration the regional level. However, as Copus et al. (2008) note Eurostat and other international and national institutions adopt different rural-urban typologies according to the level of aggregation and to the policy aims. As mentioned earlier, Eurostat (2018) has developed territorial typologies that can be divided into three main groups. These groups include grid-based typologies, local typologies based on local administrative units (LAUs), and regional typologies based on NUTS level 3. All these territorial typologies are interconnected as they share common foundational elements. These elements involve classifying population grid cells into various cluster types and subsequently aggregating this data either by local administrative units (LAU) or by regions. Beyond the regional typologies (which is considered for this work's purpose), the typology based on the Degree of Urbanisation is one of the most used for local typologies. Indeed, the degree of urbanization categorizes local administrative units (LAUs) into cities, towns, and suburbs, as well as rural areas, by considering both geographical contiguity and population density. It uses minimum population thresholds applied to 1 km² population grid cells to determine the classification. Each LAU is assigned exclusively to one of these three classes. Finally, to be thorough, the grid cells typology is briefly described. Cluster types are formed by grouping 1 km² population grid cells that exhibit similar characteristics, determined by considering both their population density and geographical contiguity. Grid cells with similar characteristics can be classified into three categories: rural grid cells, urban clusters (representing moderate-density clusters), or urban centres (representing high-density clusters).

A.3 Rural-urban typology by Eurostat and one-way ANOVA test

Figure A2: Rural-urban typologies by Eurostat at NUTS3 level. Source: Eurostat



Notes: map of Eurostat rural-urban typologies. This classification categories as *predominantly urban* those regions where more than 80% of the population live in urban clusters; *intermediate regions* as those regions where more than 50% and up to 80% of the population live in urban clusters and as *predominately rural* regions those regions where at least 50% of the population live in rural grid cells. Source: Eurostat.

Table A5: Turkey DHS test results for Eurostat categories

Simultaneous Tests for General Linear Hypotheses
Multiple Comparisons of Means: Tukey Contrasts Linear Hypotheses:

	Estimate	Std. Error	t value	Pr(>|t|)
PR - IR == 0	-0.004705	0.033173	-0.142	0.989
PU - IR == 0	0.034900	0.031452	1.110	0.508
PU - PR == 0	0.039605	0.032279	1.227	0.437

(Adjusted p values reported – single-step method)

Notes: Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

CHAPTER 2
An evaluation of the Common Agricultural Policy: a multivalued policy mix approach

Abstract

The Common Agricultural Policy (CAP) is one of the most ancient European Union (EU) policies which has evolved overtime. Traditionally, the CAP supports farmers' activities and maintains fair prices for agricultural producers and consumers; more recently, its objectives include promoting a balanced territorial development in order to reduce the rural-urban divide across and within Member States. Therefore, the CAP has turned into a policy characterised by many instruments which allow all the actors involved (farmers, MS, consumers, etc…) to adopt different implementation choices. The current study considers the CAP as a multivalued discrete treatment and infers impact causality through the Generalized Propensity Score (GPS), approach developed by Imbens (2000). Beyond the baseline treatment (Low CAP), the other CAP policy mixes are based on the access to three main types of CAP funds (Direct Payments, Market Measures and Rural Development). The analysis refers to the period 2011-2015 for the EU-28 NUTS3 regions and focuses on three outcomes (GDP per capita, Gross Value Added in Agriculture and Employment in Agriculture). Main results show that Direct Payments positively affect GDP per capita, while Market Measures and Rural Development mainly foster agricultural employment and agricultural productivity. Furthermore, another contribution of this work regards the concept of convergence between rural and urban regions which are defined in a new and innovative way.

1. Introduction

The Common Agricultural Policy (CAP) is one of the cornerstones of European Union policies. Since the 1962, this policy plays a central role in supporting farmers' activities through Direct Payments and Market Measures and, successively, in pursuing balanced territorial development goal by financing Rural Development Programmes. The historical importance of the CAP is reflected in the fact that about 38% of the total EU budget in the programming period 2014-2020 is allocated in this policy.

The CAP is introduced mainly as a market intervention whose aim is to guarantee fair prices for European agricultural producers and consumers. The policy has evolved overtime and is implemented through many reforms which move from support more linked to production to a reinforcement oriented to balanced territorial development. Originally, CAP payments are tied to production of fixed output such as crops and number of animals ("coupled payments"). The *MacSharry reform* in 1992 and the *Agenda 2000* progressively introduce "compensatory" payments not linked to production ("decoupled payments") such as basic income for farmers. In 2003, the *Fischler reform* establishes the "Single Payment Scheme" which provides subsidies tied to the land but not to the type of production or the quantity of goods produced. Furthermore, the Council Regulation 1290/2005[1] defines two distinct funds which finance the CAP: the European Agricultural Guarantee Fund (EAGF) and the European Agricultural Fund for Rural Development (EAFRD). The former (identified as Pillar 1) finances direct payments to farmers and measures to regulate market distortions such as private or public storage and export refunds. The latter (identified as Pillar 2) constitutes the support for EU Member States' Rural Development Programmes (RDPs)[2]. The latest CAP reforms (2013 and 2016) introduce more flexibility for MS in distributing resources between the pillars. Specifically, the most recent reform establishes two other new elements: "Basic Payment Scheme" and the principle of "convergence". The former innovation consists of a basic income support and other components that compensate specific farm actions (e.g., 30% of the direct support, the *Greening payments*, are linked to environmental aims) and specific status (being a young farmer, farming in areas with natural constraints, etc…). The

[1] Council Regulation (EC) No 1290/2005 of 21 June 2005 on the financing of the common agricultural policy.
[2] Pillar 1 instruments are entirely financed by the EC and applied uniformly to MS, while Pillar 2 measures are decided and co-financed by the MS. This implies high diversification in the composition of Pillar 2 across the EU NUTS3 regions.

latter novelty regards convergence both across MS (external) and within countries (internal) which consists in direct support to achieve a more equitable financing support. Especially in the period 2016-2020, as a consequence of the convergence principle, Old Member States see a reduction of the two pillars (by 13% and 18%, respectively) over the total amount of the CAP. On the other hand, New Member States experience an increase in CAP expenditure.

The aim of this work is twofold. Firstly, the current analysis intends to assess the CAP impact on socio-economic outcomes, namely economic growth, employment and productivity in agriculture. Secondly, this study wants to establish whether the CAP implementation with its increasing focus on Balance Territorial Development (BTD) is able to reduce the so-called *rural-urban divide*. EU rural areas present several imbalances with respect to urban areas in terms of GDP per capita, higher poverty rates, especially for older people, women and migrants. In addition, these areas record a decline in employment in agricultural sector and lower educational levels. For these two purposes, three outcomes have been chosen (*GDP per capita*, *GVA in Agriculture* and *Employment in Agriculture*) and they are expressed in terms of growth rates differential between NUTS3 region value and average mean value for urban NUTS3 regions within each Member States. This measure allows to capture the rate of convergence between rural and urban regions within EU countries. Furthermore, these outcomes are in line with *The Common Monitoring and Evaluation Framework* (CMEF) which points out three socio-economic impact indicators of the Rural Development Programmes (RDPs): economic growth measured as net gross value added (GVA) in PPS, employment creation measured by net additional full-time equivalent (FTE) jobs and labour productivity defined as changes in GVA per FTE jobs[3].

The CAP is a very complex policy which can be configured as various combinations of Pillar 1 instruments and Pillar 2 measures. As Esposti (2022) clearly shows, the CAP is not a program but a policy which is made of several measures interconnected to each other and should be seen as a multiple treatment. Therefore, this study aims to estimate the causal impact of four CAP mixes which are the "treatment" received by each NUTS3 regions in the period 2011-2015. This period reflects the implementation of the 2009 *Health Check*[4] (Lovec and Erjavec, 2012) which is not a

[3] European Commission, *Technical Handbook on the Monitoring and Evaluation Framework of The Common Agricultural Policy 2014 – 2020* (2017).

[4] *Health Check* is a mid-term revision of the 2003 *Fishler Reform* which sets the financial framework of the Pillar 2 transformation and the decoupling of Direct Payments to address the distortions induced by the traditional form of agri-sector income support.

proper reform, but provides instruments to further promote the decoupling of direct payments, thus allowing more flexibility to the reallocation between the two Pillars (modulation scheme). The four CAP mixes are *Low CAP*, *Predominantly Direct Payments* (PDP), *Predominantly Market Measures* (PMM) and *Predominantly Rural Development* (PRD). Hypothetically, the causal effect of the CAP mix could be estimated simply comparing the average performance whether the treatment would be randomly assigned and, therefore, regions differ only for that specific policy mix. Technically speaking, randomisation guarantees that the treatment is exogenous and treated units under a certain treatment would be a proper counterfactual for the treated ones. However, the context is different as the treatment is not randomly assigned but the policy mix is chosen by regions according to their economic characteristics and strategic necessities. For instance, regions with high land productivity are likely to have a solid agricultural sector and to implement a CAP with a high percentage of Pillar 1 instruments. Thus, a strong correlation between a mix characterized by “strong Pillar 1” and GVA in Agriculture may not represent a causal connection. Similarly, a positive correlation between a mix characterized by “strong Pillar 2” and regional economic growth may be misleading since more dynamic regions produce more ambitious Rural Development Programmes. These two examples demonstrate that a correlation exercise does not guarantee a causal interpretation; therefore, Counterfactual Impact Evaluation (CIE) methods have to be adopted in order to substitute an “ideal experiment” considering a “quasi-experimental” setting. In this context, the most appropriate method is the Generalized Propensity Score (GPS) method elaborated by Imbens (2000). The GPS provides causal estimates, assuming that the pre-treatment characteristics influencing the CAP’s implementation choices and the potential outcomes. As Rosenbaum and Rubin (1983) illustrate, the GPS balances the pre-treatment variables across the treatment groups, thus allowing causal inference by deleting systematic differences that describe treatment and outcomes. Empirically, a misspecification of the GPS can generate significant bias in the causal parameters (Kang and Schafer, 2007; Smith and Todd, 2005). For this reason, the Covariate Balance Propensity Score (CBPS) by Imai and Ratkovic (2014) is applied. This method allows to maximise the covariate balance and the prediction of treatment assignment. The rich set of pre-treatment variables, which describes regions’ profile, guarantees the correct implementation to socio-economic outcomes without high additional cost.

Existing literature about CAP evaluation is broad (Lillemets et al., 2022) and includes various methodological approaches. Most studies adopt regional input-output (I-O) and computable general equilibrium (CGE) models (Bonfiglio et al., 2016; Loizou et al., 2014). However, these types of methods allow to simply assess a correlation, not the causal impact. Although assessing a relationship of causality is preferable, only a limited number of studies try to assess robustly the causal effect of the policy using counterfactual impact evaluation (CIE) methods (e.g., Imbens and Wooldridge, 2009). These methods are very appropriate to tackle the self-selection bias. Each region (funds' beneficiary) implements a CAP mix based on its socioeconomic and geographical profiles. These features act as "confounders" of the policy's true effect. Some attempts are reported in literature and mainly focus on Pillar 2 evaluation at single Member State level (Medonos et al., 2012; Salvioni and Sciulli, 2018; Michalek et al., 2020). For instance, Bakucs et al. (2019) implement a Generalized Propensity Score Matching and a Difference-in-Differences to assess the impact of Rural Development Programme on Hungarian LAU 1 regions between 2008 and 2013. Surprisingly, authors find no significant effect or sometimes even negative impact and wonder about the effectiveness of RDP in Hungary. On the other hand, just few empirical evidence which conduct CIE analysis are reported for Pillar 1. For instance, Michalek et al. (2014) apply the Generalized Propensity Score (GPS) matching approach to estimate the capitalization of the single payment scheme (SPS) into land values. They find a 6% to 10% SPS capitalization rate which implies that, within European Union, on average nonfarming landowners' gains from SPS are only 4%.

Furthermore, most literature considers the CAP as a whole (Crescenzi and Giua, 2016; Galluzzo, 2018) or separately Pillar 1 and Pillar 2 (May et al., 2019; Bakucs et al., 2019). One of the novelties of this study lies in the fact that the CAP is considered as a whole (both Pillar 1 and Pillar 2) and it is treated as multivalued discrete treatment representing a finite set of policy implementation choices. This approach simplifies the dimensionality of a continuous multivariate treatment, maintaining the qualitative aspects linked to different mixes. In the existing literature, the inner composition of the treatment levels is often neglected.

This paper contributes to the existing literature on evaluation of the CAP, providing a broad and robust causal analysis. It is broad because each treatment design considers the totality of the CAP but, at the same time, does not neglect the heterogeneity of policy instruments and provides a guidance on the effectiveness of the CAP budget allocation and its contribution to the convergence of the EU rural areas. On the other hand, it is robust as the work adopts causal methods to estimate the Average Treatment Effect (ATE), not a simple correlation.

Following Dumangane et al. (2021), results quantify the outcomes within regions which are exposed to the different CAP mixes and show that CAP instruments differently contribute to achieve the policy aims. Researchers provide evidence that demonstrates that Pillar 1 mixes (in this case, *Very Strong DP* and *Strong CMO*) overtake the effect of *Very Low Pillar 1* on Agri GVA, Employment and Land Productivity. As far as Pillar 2 is concerned, authors find that it overcomes *Very Low Pillar 1* on economic outcomes, but not on agricultural outcomes. As far as the strategic objectives of viable food production and of supporting farmers is concerned and coherently with Dumangane et al. (2021), this analysis highlights that, overall, the CAP plays an important role in preserving agricultural jobs. Specifically, Market Measures show the strongest effect on employment and highlights the relevance of CAP's role in supporting and regulating EU agricultural markets. Furthermore, Direct Payments policy mix shows a strong and increasing effect on GDP per capita, but it does not contribute to foster employment in agriculture. Finally, Rural Development measures records positive and significant effect only on GVA in agriculture in 2016 and an increasing trend between 2017 and 2018 in terms of agricultural job safeguarding. This paper tries to do a step forward with respect to Dumangane et al. (2021) and adopts a more coherent way to determine the convergence between rural and urban areas. In this context, rural-urban regions are defined according to the taxonomy described in the first chapter of this PhD thesis.

The remaining of the paper is organised as follows. Section 2 describes the Common Agricultural Policy and its reforms in detail. Section 3 provides a literature review of the empirical studies on the CAP's impact on socio-economic outcomes and on the rural-urban divide. Then, Section 4 presents the data, the treatment design, the outcomes and the pre-determined variables derived from a Principal Component Analysis. Section 5 describes the CAP as multivalued discrete treatment and the Generalized Propensity Score methodology. Section 6 discusses the main results and, finally, section 7 concludes.

2. The CAP

2.1. Reforms

The Common Agricultural Policy (CAP) is established in 1962 and is one of the cornerstone European Union (EU) policies. The CAP is initiated after World War II within the Treaty of Rome that is signed in 1957 (Ackrill, 2000). The aim of post-war European countries is to improve food security and agricultural production in order to become self-sufficient within European boundaries. The Treaty of Rome leads the beginning to the process that sets up a common agricultural policy, aiming at establishing both guaranteed markets and fair prices for European agricultural producers and consumers. The CAP is based on four main principles. The first aim is to create a unified market for the agricultural commodities' free movement. Secondly, all CAP costs should be financed by the European Fund for Orientation and Agricultural Guarantee (FEOGA) which is a communal treasury, supported by import tariffs and European Member States contributions, in order to guarantee financial solidarity. The third principle regards the European products which should be preferred over the imported ones. Finally, farmers' incomes have to be equalized to other sectors' incomes to foster food access to the consumer[5]. The Treaty of Rome also introduces Common Market Organizations (CMOs), still existing today, which is a set of rules which regulates markets in the European Union.

As Sotte (2023) notices, the Common Agricultural Policy has evolved in tandem with the transformation of the European Union, which has established new objectives. Originally focused on opening up the internal market and safeguarding it from external influences, the CAP has now shifted its priorities towards sustainable development in an ever-changing global landscape. Adapting to the current needs has led to successive reforms of the CAP, integrating its traditional sectoral role with the territorial development of rural areas, in parallel with the European regional and cohesion policy. Simultaneously, the CAP has also been entrusted with agri-environmental responsibilities[6].

[5] The Common Agricultural Policy: a brief introduction. Institute for Agriculture and Trade Policy. Global Dialogue Meeting, 2007, Washington, D

[6] More recently, the proposal to place the Common Agricultural Policy (CAP) within an even broader strategy is gaining ground: it is worthy to conceive the CAP in accordance to other interconnected European Union strategies (e.g., the "*Green Deal*," the "*Farm to Fork*" and the "*European Biodiversity Strategy*."

The CAP has evolved overtime and many reforms have been implemented, moving from a policy aimed to stabilize prices and markets of the agricultural sector to a more complex policy with a territorial-oriented approach. It is worthy to highlight major reforms that have better pursued the stated aims in the Treaty of Rome.

The first notable reform dates back to 1992 and it takes the name of ***MacSharry reform***. At this stage, the CAP shifts from market support to farmer support by introducing direct payments. Furthermore, for the first time, the principle of sustainable development appears, encouraging farmers to become more environmentally friendly. This review introduces a system of compensatory income, replacing the system of prices protectionism. The reduction in guaranteed prices for arable crops that implies income losses is fully compensated by direct aid per hectare.

The Agenda 2000 constitutes another stage in CAP transformation. This new reform mainly focuses on four points. Firstly, EU prices have to be aligned with world prices by directly aiding producers. The second point regards the introduction of environmental cross-compliance by Member States to finance rural development measures. Another new element that characterised Agenda 2000 is the reinforcement of socio-economic structure and the relative measures which constitutes the basis for the introduction of the second pillar of the CAP which focuses on rural development policy. Finally, a strict financial framework for the period 2000-2006 is introduced aimed at budget stabilisation.

The most relevant novelty of 2003 ***Fischler reform*** is the introduction of decoupled direct payments to farmers. From this moment, direct aids to farmers should be made by one “single farm payment scheme” (SPS) per year, replacing existing direct aids. The condition for income support is to fulfil food safety, high environmental and welfare standards.

In 2009, the ***Health Check*** is implemented. It further reinforces the decoupling of aid through a gradual elimination of the remaining payments linked to production by finally implementing the SPS. Furthermore, this reform strengthens the concept of “modulation”: first pillar financial resources are moved towards direct aid for promoting rural development measures, i.e., Pillar 2.

Finally, *Health check* adds more flexibility into the rules for public involvement and regulates supply to foster farmers' ability to respond to market signals.

The ***2013 CAP reform*** discloses the *2014-2020 Programming Period* and constitutes another turning point in the CAP evolution. This stage implements new priorities aiming at promoting a more equitable distribution of direct payments to farmers and at introducing more attention to environmental aspects. Firstly, this reform targets decoupling direct payment to seven specific objectives: a basic payment, a greener payment for environmental goods (ecological component), a payment for young farmers, a redistributive payment, additional income support for areas with specific natural constraints, aid coupled to production and a simplified system for small farmers. Secondly, in this reform the two pillars have been consolidated and the flexibility among them is enhanced. Furthermore, the 2013 CAP reform introduces the so-called "external convergence" process whose aim is to guarantee a greater uniformity between Old Member States (OMS) and New Member States (NMS) in terms of direct payment. Finally, as regards rural development, a more integrated, targeted and territorial approach is fostered.

Finally, the last important step in the CAP's path is in 2016 with the ***Greening Reform*.** This phase is characterized by a general reduction of budget but an increase in environmental measures. The CAP greening reform maintains the decoupled payments as introduced in the 2003 but links them to the provision of public goods and externalities[7]. Another novelty of this reform consists in the possibility for MS to move funds between the two pillars. Member States with average direct payments per hectare below 90% of the EU average are allowed to move up to 25% of the RDP funds to direct payments[8]. The CAP greening takes up to 30% of the total direct payment funds. Another element that characterizes this reform is the special support for specific groups and for specific farming practices. Each Member States can decide to implement some instruments. For instance, payments for young farmers are introduced as mandatory and are financed by up to 2% of the direct payments. Another instrument concerns the small farmer scheme which is a voluntary payment whose aim is to reduce administrative duties and simplify small farmers' access to direct

[7] Gocht, A., Ciaian, P., Bielza, M., Terres, J. M., Röder, N., Himics, M., Salputra, G., *Economic and environmental impacts of CAP greening: CAPRI simulation results*, EUR 28037 EN, Joint Research Centre, European Commission, 2016.

[8] EU (2013), Regulation No 1307/2013 of the European Parliament and the Council establishing rules for direct payments to farmers under support schemes within the framework of the common agricultural policy and repealing Council Regulation (EC) No 637/2008 and Council Regulation (EC) No 73/2009, Official Journal of the European Union L 347/608.

payments. Furthermore, specific payments to farmers which perform own activities in areas with natural constraints are implemented. Finally, the reform introduces a mandatory reallocation funds from larger to smaller farms in order to rebalance the distribution of direct payments.

2.2 Pillars' structure and financing

The Common Agricultural Policy (2014-2020) finances expenditures on agriculture for three main purposes: to protect the viable production of food, to sustain management of natural resources and to support rural development. About 38% of EU budget is spent on the CAP.

The CAP consists of two pillars. The first one includes direct payments which are annual payments to farmers aiming at stabilising farm revenues to contrast market prices volatility and unfavourable weather conditions and market measures whose aim is to tackle specific market conditions and to foster trade. For the Multiannual Financial Framework 2014-2020 the CAP amount allocate to the first pillar is 308.72 billion euros. The second pillar includes priorities whose aim is to achieve a balanced territorial development of rural economies and to sustain the farming sector by an environmentally sustainable point of view. Pillar II is financed by the European Agricultural Fund for Rural Development (EAFRD) and counts for 99.6 billion euros for the programming period 2014-2020[9]. Article 14 of Regulation (EU) No 1307/2013 establishes an inter-pillar flexibility which means that Member States may transfer funds between the two pillars up to 15% of the original amount. For the programming period 2014-2020, the net transfer consists in 4 billion euros in order to foster the rural development.

Regarding Direct Payments (DP), they are decoupled from specific production and tend to support farmers' income. Direct payments have many purposes and are composed of three compulsory components and three voluntary components. The compulsory ones are basic payments, greening components and payments to young farmers. Basic payments per hectare are income support and are subjected to a convergence process between farmers and Member states. The aim of greening components is to compensate for crop diversification, for maintaining ecological area and for protecting permanent pasture costs. This constitutes a remuneration for providing environmental

[9] European Parliament, (2016). How the budget is spent. EPRS | European Parliamentary Research Service. Authors: Marie-Laure Augère-Granier, Gianluca Sgueo. Members' Research Service PE 586.623

public goods which are not remunerated by the market. Member States have to allocate 30% of direct payment to finance greening component. Finally, payments for young farmers consists in additional income for five years for the first 90 hectares of the farm. Member states have to allocate 2% of the direct-payments to young farmers. On the other hand, voluntary components are a redistributive payment, additional income support for areas with specific natural constraints and a specific support coupled to some production. Firstly, the redistributive payments is provided for the first hectares of their farm: up to 30% of the MS direct payments. Secondly, up to 5% of the direct payments may be addressed to areas with specific natural disadvantages. Finally, up to 15% of direct payments may be allocated to specific areas or types of farming with social and/or economic difficulties to foster some productions.

As far as market measures are concerned, they follow the single Common Market Organisation (CMO) which is financed for 2.7 billion euros in 2016. The first market measures regard the marketing of agricultural products (e.g. geographical indications), rules on State aid, the functioning of producer organisations and competition rules applicable to enterprises. A second block of market measures includes general provisions about exceptional measures mainly concerning market fluctuations or market support in case of outbreaks of animal diseases or consumers' confidence loss. The third type of market measures covers specific sectorial programmes (e.g. wine, oil, fruit and vegetables). The fourth typology consists in a crisis reserve fund of 400 million per year euros whose aim consists in protecting financial resources to allocate in case of agricultural sector crisis. These resources are stoked through the so-called "financial discipline" mechanism: deductions from direct payments are reimbursed to the same farmers in successive financial years. Finally, other market measures include issues tied to international trade and competition rules.

The primary objective of the Pillar II is to establish a policy that prioritizes the development of regional (rural) areas rather than focusing solely on the agricultural sector. The role of EU rural development policy is to help more disadvantaged areas in facing problems like low income levels, lack of services and infrastructure, depopulation and lack of opportunities in particular for women and young people. The mission of European Agricultural Fund for Rural Development (EAFRD) is to reach a smart, sustainable and inclusive growth "*by promoting sustainable rural development throughout the Union in a manner that complements the other instruments of the CAP, the* *cohesion policy and the common fisheries policy*"[10]. This mission is disentangled into three main objectives: fostering the viable food production, ensuring sustainable management of natural resources and climate action and achieving balanced territorial development. In turn, these objectives are translated into six priorities:

1. Fostering knowledge transfer and innovation in agriculture, forestry and rural areas
2. Enhancing farm viability and competitiveness of all types of agriculture, and promoting innovative farm technologies and sustainable management of forests
3. Promoting food chain organisation, animal welfare
4. Restoring, preserving and enhancing ecosystems
5. Promoting resource efficiency and supporting the shift toward a low-carbon and climate-resilient economy in the agriculture, food and forestry sectors
6. Promoting social inclusion, poverty reduction and economic development in rural areas

In turn, each of the six priorities is broken down into focus areas to address specific intervention (Art. 5 of Regulation No 1305/2013).

Pillar II is implemented through *Rural Development Programmes (RDPs)* in each EU Member State. RDPs are documents drawn up by countries and regions, setting out priority approaches and actions to meet the needs of the specific geographical area they cover. Additionally, the RDPs need to address *at least four of the six EU Rural Development priorities*. In the 2014-2020 programming period, there are *118 national and regional RDPs* funded through the *European Agricultural Fund for Rural Development (EAFRD) and national contributions*. In the current seven-year period, approximately € 100 billion through the EAFRD and € 61 billion of public funding in the Member States is being spent on rural development.
The effective delivery of the RDPs falls within the responsibilities of national or regional public authorities: *Managing Authorities* (MAs). This is further supported by designated *Paying Agencies* (PAs), tasked with making payments to project beneficiaries. The European Commission itself does not allocate funding to beneficiaries; it shares RDP management responsibility with the MAs and reimburses programme authorities through the EAFRD for the payments made by the PAs.

[10] Art. 4 Regulation (EU) No 1305/2013

3. Related literature

This paragraph reviews two main streams of literature. Firstly, most relevant and recent evidences regarding the Common Agricultural Policy impact and effectiveness on economic, social and environmental outcomes are illustrated. Secondly, a particular focus is dedicated to the rural-urban divide.

As it is shown in Section 2, the EU's Common Agricultural Policy is one of the most ancient EU policies and the political instrument to provide financial support to agricultural producers. In fact, the CAP takes a large share of total EU expenditure, even if share of CAP budget has decreased from 1980 to 2020 by 31% points (DG Agriculture and Rural Development, 2021a). The CAP is a very complex policy, therefore, most times, only single instrument or measure are analysed in the existing empirical studies. As Lillemets et al. (2022) note, for instance, rarely socio-economic impacts are evaluated. The authors, who compute a systematic literature review, claim that the reasons behind this shortcoming are manifold. First of all, some researches are discouraged by the lack of data: regional data on socio-economic variables are more difficult to find, except for employment data. Furthermore, investigating socio-economic impact on rural development variables lays difficulties since it is a vague concept that is exposed to many interpretations. In fact, thinking, for instance, at specific CAP measures regarding ICT infrastructure, it is clear that financial resources destinated to this measures are too small to link effects to that specific measure. In addition, another problem of impact evaluation may concern in isolating the effect of CAP from other EU policies such as Cohesion Policy which contributes to socio-economic development of rural areas (Crescenzi and Giua, 2020).

Although a systematic literature review on socio-economic impact of the CAP does not exist, some attempts have been made by Erjavec and Lovec (2017) and very briefly in OIR Gmbh et al. (2021); beyond the already cited Lillemets et al. (2022). In addition, both Shuh et al. (2016) and Vigani et al. (2019), limited to employment outcome, produce a systemic review of literature. As it is possible to deduce, the existing empirical works touch upon many topics concerning CAP which differ in terms of type of intervention, considering the CAP as a whole or specific measures and instruments, varying based on the outcome variables and by the level of territorial units and methods adopted.

The socioeconomic impacts of the CAP can be measured through different outcomes. Regarding the economic perspective, GDP and GVA are usually used as a proxy for economic development. For instance, Psaltopoulos et al. (2006) consider three Greek regions and three types of CAP measures (farm income support, aids to increase agricultural productivity and aids to economic diversification) and demonstrate that these measures, overall, have an impact between 0.01% and 1% on regional economy in a ten-year period. However, not all the three regions react in the same way: the region of Archanes registers an increase of 4.3% in farm income support, a higher percentage comparing to 0.8% and 0.1% recorded in Kazabtzakis and Heraklion, respectively. A similar situation is recorded in Czech Republic by Bednatikova (2015) who highlights an increase of 0.3% of regional production. In Slovenia, Juvancic et al. (2005) show a positive CAP impact due to an increase in service sector output. Looking at the impact on the GDP, many studies demonstrate that CAP subsidies bring benefits on EU Member States economic development. Zawalinska (2009; et al., 2013) shows that in Poland GDP is boosted by CAP measures for a percentage between 0.07% and 0.3%, exception for investment funds in construction which increase by 5.3%. In Italy, mainly Pillar 2 has a positive effect on GDP in the programming period 2003-2007 (Salvioni and Sciulli, 2011) and a combination of five Pillar 2 measures in the following programming period (2007-2013) increases by 0.1% the GDP (Felici et al., 2008). As Esposti (2017) notes, studying 15 EU countries between 1989 and 2000, CAP measures have positive effects on economic outcomes, but this effect is very small (i.e. less than 0.01%). In addition, Crescenzi and Giua (2016) highlight a small effect on GPD growth in relation to both Pillar 1 and Pillar 2, analysing 12 countries between 1994 and 2013. Concerning the CAP impact on regional GVA, the most relevant studies estimate the effect of some rural development programme (RDP) and come to the same conclusion that is they have a positive effect. Castano et al. (2019) take into consideration Scotland, Ireland and Portugal, while Ozolins et.al (2015) refers to Latvian investments in RDP. Overall, it is possible to claim that existing literature show a positive CAP impact on the economy, but often negligible looking at total output, GDP and GVA (Lillemets et al., 2022).

Another frequent outcome when socioeconomic CAP impact is analysed is employment. This branch of literature is various and depends on the context. In fact, Psaltopoulos et al. (2006) demonstrates that in Greece the CAP impact on employment varies between 1988 and 1998 according to the measures and regions taken into account, recording a range that goes from 0.2% in Heraklion to 8.6% in Archanes. However, most times the impact on employment highlights a small and negligible effect. For instance, Zawalinska (2009) shows that direct payments increase by just 0.1% rate of employment in Poland between 2004 and 2008, while Mantino (2017) demonstrates even a negative impact of direct payments in Italy on farm employment. One possible explanation could be the introduction of decreased labour conditions or to risk-averse farmers' behaviour who benefits from subsidies. As previously mentioned, the effects of CAP impact on employment varies also according to the areas of intervention. For example, both Petrick and Zier (2011) and Zawalinska et al. (2013) demonstrate that subsidies to Less Favoured Areas (LFA) have no effect or negligible impact on employment, respectively. Looking at Rural Development Programme (RDP) measures, most studies report a positive impact on employment (Lampiris et al., 2018; Mantino, 2017; Mattas et al., 2008); on the other hand, Salvioni and Sciulli (2018) do not observe an impact of RDP on unemployment rate for the programming period 2007-2013 in Italy. However, different types of RDP tools have different impact. In fact, it is possible to notice that investments in modernisation and technology seem to increase employment in Italy (Mantino, 2017), in Greece (Bournaris et al., 2014) and Poland (Zawalinska, 2009), whereas Petrick and Zier (2011) find that such measures lead to job losses in three German regions. This result can be justified by the fact that usually technological developments imply the substitution of human workforce. On the other hand, agri-environmental measures have an opposite effect because they foster labour-intensive technologies (Midmore et al., 2008; Petrick and Zier, 2011). Looking at Pillar 2, measures finance projects whose aim is to foster enterprises' development and diversification in economic terms. This type of intervention has, as a consequence, the creation of non-agricultural jobs (Lillemets et al., 2022). Therefore, it is possible to claim that the CAP generates both direct and indirect effects, although most times identifying the right number of jobs created by the CAP measures is hard to establish. For instance, Dudek and Karwat-Wozniak (2018) highlight that in Poland, despite the effort to create non-agricultural jobs due to the CAP funds, rural employment rate does not increase significantly. By contrast, Klepacka et al. (2013) highlight how two target subsidies (crop and LFA) and decoupled payments available for all farms have a positive effect on hired paid labour. In addition, Florina (2020) shows how European funding has affected rural entrepreneurship development in Romania. In fact, investments in purely non-agricultural activities will create new jobs and lead to the absorption of agricultural sector labour surplus. Also Ozolins et al. (2015) highlight the importance of fostering non-agricultural activities in order to diversify rural economy which is affected by a decrease in agricultural and forestry employment. Authors suggest that in Latvia one potential solution to support rural entrepreneurship is gathering EU funds in small companies in rural areas because those territories have no capacity to develop large projects. Midmore et al. (2008) focus on employment impacts of Pillar 2 in six different rural areas of EU Member States in the programming period 2000-2006. Authors' purpose is stressing how CAP impact on employment could be indirect. For instance, varying activities in the long run could originate the decline in women's participation in agriculture and widespread job opportunities.

A sub-stream of research about rural employment focuses on farm labour migration and the movement of workers from agriculture to other sectors. Generally, the CAP has the effect of preserving labour force in agriculture. However, it is opportune to make a distinction between Pillar 1 and Pillar 2 payments. For instance, Olper et al. (2012) take into consideration labour out-migration from agricultural sector determinants across 149 EU regions over the 1990-2008 period. They find that the CAP funds significantly contribute to create jobs in agriculture; in particular, Pillar 1 subsidies generate an effect twice greater than Pillar 2. Also Tocco et al. (2013) suggest that total CAP subsidies at regional level decrease the out-farm migration of agricultural workers; however Pillar 2 in some cases generate an increase in out-farm migration. Furthermore, another distinction has to be made regarding labour flows between new and old Member States. Tocco et al. (2013) highlight a positive effect for Hungary and Poland, while for Italy and France no-significant results are reported.

In addition, another recurring distinction is described between family and hired labour force. For instance, Salvioni and Sciulli (2011) find that farms which receive at least a RDP payment increase family labour, while total labour employed on farm does not increment. Bartolini et al. (2015) highlight a similar effect with respect to direct payments in Tuscany farms: they increase family labour, but they are negligible for hired labour. Furthermore, some evidences demonstrate that the CAP impact on employment may generate regional spillover effects. These effects could be either positive or negative, freeing labour force from agriculture or providing new job chances (Benga et al.,2017; Bonfiglio et al., 2016).

Overall, the CAP effect on employment is demonstrated to uphold agricultural employment and to create rural jobs (Schuh et al., 2016). However, it depends on policy instruments: Garrone et al.

(2019) show that CAP subsides decrease labour outflow from agriculture, but almost totally due to decoupled Pillar 1 payments.

Relevant works in literature also describes less frequently outcomes. Firstly, very few evidences assess the CAP impact on the number of people living in rural areas. Most studies demonstrate that CAP income support helps farms to survive, however CAP subsidies are not able to influence migration in rural areas. For instance, Bakucs et al. (2019) focus on RDP 2007-2013 expenditures in Hungary and fail to demonstrate that the increase in a migration-based Quality of Life Index is due to RDP expense.

Another important aspect is the CAP impact on rural development. In literature, the concept of rural development is vague and broad (Abreu et al., 2019), but works usually calculate composite indicators or adopt some proxy variables which investigate the interaction between CAP expenditure and rural development on a regional level. The most popular example is represented by Michalek et al. (2012) who uses a rural development index composed of 21 indicators to measure the effect of the SAPARD programme on rural development in Poland and Slovakia. The researchers find that the programme positively affect rural development in Poland, whereas the effect is negligible in Slovakia. Some studies evaluate rural development in terms of regional cohesion, more specifically, looking at disparities within EU regions.

One stream analyses how regional imbalances are affected by the CAP starting from initial distribution of funds. For instance, Bonfiglio et al. (2016) find that most CAP spending is concentrated in rural and intermediate regions in EU 27. In addition, Zawalinska (2009) shows that in Poland poorer regions assimilate more funds relative to GDP, whereas in Czech Republic Pelucha et al. (2017) point out that more socioeconomic developed municipalities receive more funds from LFA payments and agri-environmental measures. Overall, economic convergence among regions is a quite debated topic. Both Esposti (2007) and Bonfiglio et al. (2016) identify a positive influence of CAP expenditure, respectively due to Pillar 1 and to the total CAP. On the other hand, other works focusing on a single country show an opposite effect. For instance, Hansen and Herrmann (2012) evidence that CAP expenditure does not influence income convergence in Germany and Chmielewska (2009) highlights how regional imbalances do not decrease through direct payments or RDP expenditure due to their small amount. Pelucha et al. (2017) even show that agri-environmental measures have a negative effect on socioeconomic cohesion in Czech

Republic. One possible reason to explain the incapability to reduce regional disparities is provided by Crescenzi and Giua (2016): European Cohesion policy has a positive impact on economic growth in all regions, however it is stronger in already economically more advanced regions and it is optimized when its expenditure is complemented by CAP funds. Whereas, the top-down CAP measures improve regional growth in most deprived areas. Another interesting finding that appears in evaluations CAP impact on regional cohesion and convergence is related to spillover effects. In fact, Bonfiglio et al. (2016) demonstrate that allocating CAP funds to rural regions bring economic benefits also to wealthy urban regions in several EU countries. Also Psaltopoulos et al. (2006) note the same trend in three Greek regions: CAP expenditure in the two rural regions taken into account leads economic advantage to the urban area under study.

Looking at the methodological perspective and focusing only on quantitative methods, most studies that aims to assess CAP impact, implement regional input-output (I-O) and computable general equilibrium (CGE) models. For instance, Bonfiglio et al. (2016) apply a multiregional Input-Output model at NUTS3 level and demonstrate that CAP impact does not depend exclusively on the initial allocation of the funds but also on interregional and intersectoral links. Loizou et al. (2014), employing regional Input-Output model, try to capture impacts on local output, employment and household income. These models help to analyse relations among different economic activities within a region and to assess the effects of shocks.

Only few studies use counterfactual impact evaluation (CIE) methods which are able to determine the causal impact of the policy. As it is widely explained by Michalek (2012), this is likely to mainly depend from the fact that most times it is difficult to identify a control group because CAP funds are potentially allocated to all regions and no precise eligibility criteria have to be fulfilled. Therefore, the counterfactual outcome has to be estimated by statistical methods as it is usually not observed. In particular, a limited number of works apply CIE methods on Pillar 1 impact analysis. For instance, Petrick and Zier (2011) adopt a difference-and-differences approach to examine employment effect in three German regions. Authors find that farms investments aid and transfers to less favoured areas have no marginal employment effect. In addition, Esposti (2016) shows that Pillar 1 after the 2003-2005 EU CAP reform actually has a different (in some cases, even opposite) effect in re-orienting farm production choices in comparison to investment decisions in Italy. Furthermore, Michalek et al. (2014) apply the Generalizes Propensity Score and look at the capitalization of the Single Payment Scheme (SPS) into land values in 15 EU countries. They find that on average, within European Union, nonfarming landowners gain from Single Payment Scheme (SPS) only 4%. However, authors observe that the capitalization rate varies according to SPS levels and across Member States.

On the other hand, counterfactual impact methods are more common in evaluating the impact of Pillar 2. For instance, Salvioni and Sciulli (2018) adopt a conditional difference-in-differences approach to the 2003-2007 FADN survey in Italy to evaluate growth-oriented measures of the Rural Development Programme (RDP) on farm income, employment and partial productivity and find that no evidences emerge. By contrast, a productivity increase is recorded participating in specific policy schemes which foster farm performance. Furthermore, Michalek et al. (2016) investigate the magnitude of substitution of firm investments with investments support policies financed by RDP in Germany. Authors employ the difference-in-differences propensity score matching methodology to a panel data of 1333 firms and find that firms use public investments to substitute private funding. This methodology is suitable because it addresses selection bias and misspecification of functional form. The same methodology is recorded in Bakucs et al. (2019) employ GPSM and difference-in-differences methods to measure the impact of RDP on Hungarian LAU regions' well-being. The authors conclude that the impact is not significant and, in some cases, even negative. Recently, Michalek et al. (2020) apply a generalized propensity score (GPS) matching to assess food processing support at regional level in Poland and point out that RDP brings structural change in food sector. In addition, basing on Propensity score matching and dose response treatment models, Mack et al. (2020) observe that RDP funds do not foster the creation of new enterprises in Romanian rural areas in the period 2009-2014. Nevertheless, they find that the higher the treatment intensity, the higher the number of new firms. Finally, Dumangane et al. (2021) infer causality applying the Generalized Propensity Score matching to the CAP considered as a mix of policies at NUTS3 level across European Union. The researchers analyse the causal effect of different CAP mixes on the regional economic performance and on agricultural sector in two different periods. They find CAP effectiveness on employment and GVA for both the whole economy and the agricultural sector and they are also able to capture the effect overtime and demonstrate that is structural. They stress the fact that CAP mixes based on Market Measures and Direct Payments produce a better result on agricultural outcomes, confirming the CAP relevance in supporting farmers.

Another important issue is examining the socioeconomic CAP impact as a whole policy or taking into consideration specific instruments of the CAP. For instance, Garrone et al. (2019) find that, on average, CAP subsidies reduce the outflow workforce from agriculture and, in this case, the effect is due to decoupled Pillar 1 payments. Furthermore, Espinosa et al. (2014) consider the rural and urban divide in terms of whole CAP effects within six NUTS3 regions in order to separate rural and urban policy effects. They construct a bi-regional (rural-urban) CGE model to assess ex-ante the impacts of two potential CAP reform scenarios ("Reduction in Pillar 1 payments" and "Rebalancing scenario"). The authors derive that CAP support to rural areas varies widely across European Union, even independently from agricultural sector development.

In addition, Rizov et al. (2018) examine whether the effect of the CAP payments on non-farm jobs creation and find positive spillovers, in particular due to Pillar 1. On the other hand, differentiating among specific CAP instruments may occur between measures or even Pillars. In the former case, for example, Pelucha et al. (2017) focus on agri-environmental measures and assess the relationship between them and the territorial cohesion in Czech Republic. In the latter case, Mack et al. (2020) take into consideration Pillar 2 and assess how RDP funds cause the increment in number of new enterprises in the treated rural communities in Romania in the programming period 2007-2013.

Finally, it is possible to observe studies that consider both European countries as a whole and within single Member States. In the first case, Tocco et al. (2013) investigate the determinants of exit from agricultural sector in France, Hungary, Italy and Poland in the period 2005-2008 and find that total subsidies decrease the outflows migration of agricultural workers from farms in the two New MS. On the other hand, Mantino (2017) analyses employment effects of the CAP in Italian agriculture and discovers that trends in agricultural employment differ greatly according to the type of socio-economic system.

Overall, it is possible to claim that, within literature on the CAP evaluation, it is worthy to provide an analysis that measures the performance of the CAP at EU-level exploiting counterfactual methodologies and that is able to measure the effectiveness of multiple CAP instruments. This work tries exactly to fill this gap in literature.

The other wide stream of literature that is taken into consideration for this work's purposes regards rural-urban divide.

A recent report by European Parliament (2017) highlights the main criticalities that rural areas have to face and that intensify the gap with urban areas. Firstly, rural areas suffer from an unfavourable demographics: in 2016, 61 million people aged 15-64 years live in predominantly rural areas, a downward figure compared to 2008 when people were 68 million. Moreover, people over 65 increase by 28% since 2005. Secondly, rural areas are characterized by a limited access to education. In fact, only 18.4% of rural population has tertiary education compared to 33.2% in cities and 23.3% in intermediate areas. Thirdly, another feature of rural areas is the weak labour market: the unemployment rate raises from 7% to almost 11% in rural areas in only four years (from 2008 to 2012). Furthermore, remoteness and low density constitute another critical issue for rural zones; 12.2% of the population faces difficulties to access public transport in rural areas, as opposed to 5.7% in intermediate areas and 2.3% in cities. Moreover, also access to healthcare and social services represents a disparity between rural and urban areas as rural population is usually further from major hospitals with respect of city inhabitants. Finally, although broadband coverage in rural areas has improved recently, the digital divide remains wide across the European Union and figures are still discouraging; 23% of people living rural areas have never used internet in 2015, as opposed to 12% in cities. Generally, the widest digital gap between rural and urban regions is recorded in south-east European countries such as Romania, Bulgaria and Croatia.

In the European Union territory, rural and urban areas are linked via *two-way flows* of people, goods, services (e.g. environmental) and money and interact to each other (European Parliament, 2017). Nevertheless, according to the EUROSTAT definition of rurality and urbanisation, wide differences still exist between these two territorial typologies.

The dimension of the rural-urban gap is analysed in literature under several points of view which include education, income, wage and political attitudes. For instance, Shucksmith et al. (2009) examine urban and rural differences in housing conditions, education, employment, access to institutions and services looking at the European Quality of Survey Index (EQLS). Authors distinguish between new and old member states and find that, overall, the richest countries show little differences between urban and rural areas, while poorest member states of east and south Europe highlight a lower level of perceived welfare and quality of life. For instance, regarding income and deprivation, within richest countries, an urban household earns about 1300 euro a month compared to a rural household who earns 1200 euro monthly. But, as average income decreases, rural-urban differences raise with lower income in rural areas in the lower-income country cluster. A similar pattern is observed in terms of deprivation: only in the poorer countries it is significantly higher in rural areas. Furthermore, access to education highlights the differences between urban and rural areas. In fact, educational level of urban people are higher than in rural areas across Europe: 25% of rural inhabitants have only primary education (compared to 18% in urban areas) and only 13% have a university degree (compared to 22% in urban areas). Finally, the EQLS includes also interesting questions about unemployment and job satisfaction. Generally, the rate of unemployment is higher in poorer countries. However, in richer countries unemployment is greater in urban regions rather than in rural areas.

Another way to measure the rural-urban divide is in terms of wage. For instance, Artz et al. (2016) disentangle observed rural-urban log wage gaps for 101 countries into the proportion explained by skill differences and the unexplained proportion. They find that on average eliminating unexplained rural-urban wage gaps increases per capita GDP by 13,9%. Furthermore, unexplained rural-urban wage gaps are greater in countries with less political systems, higher marginal tax rates and higher urban educational levels, but lower in countries with larger government shares of GDP.

As prefaced before, another important issue analysing the rural-urban divide is inequality and social inclusion. Camarero and Oliva (2019) illustrate how global financial crisis and economic recession has threatened rural areas, especially in Southern Europe, enhancing regional disparities. The researchers indicate accessibility and mobility as key factors of rural decline which sharpen social exclusion and cohesion. Rural-urban divide is also measured in terms of lack of services and access to infrastructure. For instance, Whitacre and Mills (2007) find that in the United States rural-urban differences in network externalities and income drive the high-speed gap, but not due to infrastructure, but not due to infrastructure. Furthermore, the rural-urban gap is also recorded in terms of life expectancy by Abrams et al. (2021). Authors exploit data from the Centers for Disease Control and Prevention about US deaths in the period 1999-2019. They show that, even if at a slower rate, life expectancy in rural areas still remains lower with respect to urban zones.

In addition, rural-urban divide is analysed in terms of political attitudes and behaviour. Scipioni and Tintori (2021) investigate how rural-urban divide may correlate European's opinions choices. For instance, they observe that in Member States, where EU integration and liberal immigration policies are favoured, a larger share of votes is concentrated in urban rather than in rural areas. However, in the Standard Eurobarometer survey they do not find significant differences among respondents on levels of trust towards EU and national institutions based on own level of urbanisation. More interestingly, they highlight a rural-urban divide grouping by country, region or level of urbanisation but they note that, holding constant socio-economic features (e.g. age, education and occupation), differences disappear. Therefore, it is possible to claim that variations are likely to be by-product of the structural dissimilarities of population's characteristics between rural and urban areas. Furthermore, Mettler and Brown (2022) observe how living in a rural or in an urban areas shape the political preferences in the United States. They claim that rural-urban divide fosters political polarization and vulnerability of democracy, leading to an "us" versus "them" dynamics.

As far as the rural-urban divide is concerned, another important distinction has to be done between developed (illustrated until now) and developing countries.

Most studies analyse the rural-urban gap in developing countries, especially China in the late 90s and early 00s. For instance, Wang et al. (2020) analyse the urban and rural development levels (URDL) in China through the United Nations Development Program-adjusted Human Index (HDI) to measure the balancing economic development between rural and urban areas. Authors illustrate many findings. Firstly, they propose the "inverted U" curve for the difference of URDL in China, which shows that China experiences a path which starts from expansion (1995-2001), passing through high fluctuation (2001-2011) and concludes with continuous convergence (2011-2017). Secondly, the expansion period depends on the increase in the gap between the Health Index, the Education Index and the Income Index. The decline in the gap between educational levels and in life-expectancy brings China to a period of convergence. Thirdly, from a spatial evolution perspective, the gap of URDL is quite good in the middle and northeast, but there is still room for balance's improvement in the west. Previously, also Wang et al. (2013) observe how China's fast growth is accompanied by wider rural-urban divide and increasing inequality. They examine several dimensions of divide (income, consumption, employment, health care, access to public services, etc…) and conclude that the main causes of the divide are China's urban-biased development plan and the resulting absence of social provision public goods in rural areas. More recently, Meng and Zhao (2018), adopting a binary logit and a multinomial logit methods, study the rural-urban migration in China and find that land holding in rural areas decreases the probability of permanent migration to urban areas but not the temporary decisions.

Furthermore, Hnatkosva and Lahiti (2012) describe Indian rural and urban disparities in terms of occupation, consumption and wages and educational attainment. They adopt a household survey data (National Sample Survey) in the period 1983-2010 and show a significant convergence between individuals in rural and urban areas. However, individual features seem not to determine a huge part of this convergence. In addition, authors evaluate the effect of the program NREGA which is introduced in 2005 and highlight that its impact on rural-urban wag and consumption is negligible. However, they use a state level analysis, thus it is difficult to consider this measurement a causal relationship.

Finally, Yaya et al. (2019) examine the rural-urban divide in sub-Saharan Africa countries in terms of childhood mortality and disentangle factors that mainly contribute to Under-5 mortality rate. They observe substantial differences in the outcome of interest among areas, almost 44% and 75% in urban and rural regions, respectively. Maternal age, education, maternal use of media (TV, newspaper), household wealth index, total children born, and employment status are factors that explain rural-urban gap in the selected Sub-Saharan countries.

The current work tries to enrich also this stream of literature and the aim is twofold. Firstly, the study proposes a new definition of rurality and, consequently, provides a redefinition of the boundaries of rural and urban divide. Secondly, counterfactual impact evaluation method proposed in this study is not frequent thus, this study constitutes a novelty in this field of research.

4. Data

Data exploited in this analysis refer mainly to NUTS3 level of aggregation. In some cases, part of the NUTS3 regions are aggregated because of their small dimension in order to produce a more homogenous territorial representation of EU-28. This approach is justified by the so-called *Modifiable Area Unit Problem* (MAUP) "scale effect" phenomenon (e.g. Wong. 2004): boundaries of certain areas are often set artificially based on administrative scale or historical reasons. Some NUTS3 regions are extremely small, whereas other areas tend to consider urban centre within in as a separate unit (e.g., Poland). In such cases, CAP funds allocation may not correspond to the target area where the policy is implemented, generating sever bias in the analysis. Therefore, in this study OECD territorial methodology (OECD, 2021) is followed and some regions of the Netherlands, Belgium, the United Kingdom and Germany are taken into account at NUTS2 level. Overall, this study adopts NUTS 2016 version and counts 797 regions.

The period of analysis goes from 2011 to 2015. This time span does not correspond to a Programming Period on purpose in order to catch a reform-based perspective. In particular, in 2009 the *Health Check* promotes the Decoupling of direct payments and the modulation scheme which allows financial resources transfers among the two pillars. Dumangane et al. (2021) show that in the period 2011-2015 73% of EU-28 regions increase the Decoupled to Coupled Direct Payments ratio and 80% of the regions raise the share of Pillar 2 expenditure with respect to the 2007-2014 time period. Therefore, choosing this period of analysis, this study aims to evaluate the CAP effectiveness after the 2009 Health Check.

Furthermore, given the differences in the two Pillars' nature, the funds (the treatment) are measured with respect to different economic aggregates. Pillar 1, which is characterized mainly by direct payments to farmers and measures aimed at market stabilisation, is calculated as the ratio to the average Agri-GVA (in PPS). On the other hand, Pillar 2 funds, which are made of measures whose final purpose is to foster rural development, as the ratio to the average total GVA (in PPS)[11]. CAP funds are quantified using intensities to ensure comparability between regions and determine

[11] By expressing Gross Value Added (GVA) in Purchasing Power Standards (PPS), variations in price levels between countries are eliminated.

their significance for the regional economy and the agricultural sector, which is the primary recipient of direct payments under Pillar 1.

In both cases, the average GVAs are computed from one year before the CAP implementation (that is 2010).

Since the aim of this work is to assess the socioeconomic CAP impact on balanced territorial development in the EU-28, three specific outcomes are chosen: *GDP per capita*, *GVA in Agriculture* and *Employment in Agriculture*. The outcomes are measured as growth rates between the beginning of the period and, in order to capture time effects, *t+1*, *t+2* and *t+3* (where *t*=2015). Furthermore, outcomes are measured as rates of convergence which means that they are calculated as the difference between a NUTS3 region's growth rate and the mean of the urban regions' growth rates within a specific country. Rurality and urbanity concepts are determined according to definitions of rural and urban areas proposed in the first chapter of this PhD thesis.

The empirical strategy relies on the capacity to identify a set of control variables that satisfy the weak unconfoundedness assumption (Imbens, 2000). Following Montezuma et al. (2021), this set of pre-treatment variables is chosen to show the multidimensionality of the regions, one year before the period taken into account (that is 2010). These variables include variables that describe local economy, agricultural sector indicators, demographic indicators, innovation indicators and remoteness and geographical indicators. For this analysis the set of pre-treatment variables is derived from two clustering exercises based on a Principal Component Analysis (PCA) on eighteen variables for Multidimensional approach and seven variables for Agri-sector based approach, respectively, whose aim is to characterize the regional dimension of the CAP. In the appendix, a complete description of the pre-treatment variables, the description of the clusters for both approaches, a table of a descriptive statistics of variables are added.

Although typically PCA is adopted to reduce dimensionality of multivariate analysis, in this study, it is also applied to provide a way of recognising patterns aiming at grouping NUTS3 regions that take similar CAP funds implementation decisions. In the appendix, Table A1 and Table A2 summarise through heat map visualization the average values index of the variables used in the PCA analysis for both Multidimensional Clusters and Agri-sector based clusters. According to the input variables, the four multidimensional clusters are named as follows: *Depleting regions with mixed economies*, *Attractive forested regions with low agricultural productivity*, *Developed highly* *innovative semi-urban regions* and *Semi-urban regions with large and developed agricultural areas and sector*. While the four Agri-sector based clusters are labelled: *Traditional low productivity agricultural sector*, *High labour productivity agriculture*, *Artificial areas with high productive land use* and *Forest areas with low labour productivity*.

Dunteman (1989) provides an extensive review of the use of PCA in cluster analysis. The Principal Component Analysis aims to reduce a large set of variables into a smaller one maintaining as much information as possible from the original dataset. The algorithm of PCA work as follows. The first step is the standardisation of the input variables in order to homogenize the scale. The standardisation is obtained subtracting the mean from each value of each variable and, then, dividing by standard deviation. The second step consists in computing the covariance matrix which shows the correlation among all possible pairs of variables. High correlation means that the information included in the two variables is redundant. The third step consists in calculating eigenvalues and eigenvectors of the covariance matrix to identify the Principal Components (PCs). The PCs are new variables that are combinations of the initial variables and gather the variables that contain most information (maximum amount of variance). Eigenvectors are arranged in descending order based on their eigenvalues which represent the amount of variance of initial variables. Finally, the last step consists in remodelling the data reorienting them along the PCs axes including the new variables. Therefore, the final dataset is obtained by multiplying the eigenvectors matrix with the standardised values matrix. Table 1 and Table 2 show the Principal Components of Multidimensional and Agri-sector based approaches. They are extracted applying the Guttman-Kaiser criterion which means keeping the PCs that explain 70-80% of the cumulative variance. The PC loadings are the correlation coefficients between the original variables and the PCs. This work utilizes Ward's criterion[12] in hierarchical cluster analysis after performing principal component extraction. The criterion is employed to determine which pair of clusters should be merged at each step, aiming to minimize the variance within the clusters.

[12] The agglomerative hierarchical clustering process begins by considering each observation as a separate cluster and then iteratively merges the similar clusters until a single large cluster containing all observations is obtained. During this process, Ward's criterion evaluates the contribution of the various mergers and chooses to merge the clusters that minimize the sum of squares of the intra-cluster distances.

Table 1. Principal Component loadings for Multidimensional approach

Variable	PC1	PC2	PC3	PC4	PC5	PC6
GDPpc(PPS)	0.3803	-0.1011	0.1594	-0.0117	-0.1095	0.1176
GVA Agri per Emp	0.1782	-0.3119	0.2132	0.1308	0.4158	-0.2049
GVA Agri per AA	0.2214	0.2139	0.1071	-0.0897	0.5594	-0.2819
Empl per AA	-0.0102	0.4703	-0.1264	-0.176	0.0527	-0.2722
GVA share Agri	-0.2874	0.1847	-0.1053	0.1315	0.4215	0.0324
GVA share Ind	-0.1101	-0.0642	-0.1277	-0.3974	-0.1695	0.252
Pop dens	0.3458	0.2832	-0.1374	0.0103	-0.0674	0.0121
Birth rate	0.1598	0.1452	-0.0513	0.3566	-0.277	-0.2961
Net migr	0.1857	-0.1151	0.1811	0.198	-0.0689	-0.3069
EU TM	0.3691	0.15	-0.0619	-0.056	0.1095	0.3491
CD	0.3367	0.1085	-0.066	-0.1125	0.1838	0.4007
Forest	-0.123	0.1306	0.5447	-0.3271	-0.062	-0.0531
Artificial	0.3487	0.2335	-0.1902	0.0109	-0.1701	-0.0988
AA	-0.0505	-0.2643	-0.506	0.3128	0.1575	0.0948
MEGA1	-0.2188	0.3906	0.0416	0.3962	-0.03	0.1282
MEGA2	-0.1471	0.0809	-0.2764	-0.3183	0.2516	-0.0796
MEGA3	-0.1911	0.3597	0.2415	0.2655	-0.0011	0.2799
MEGA4	0.0734	-0.0923	0.2941	0.2291	0.1986	0.3727

Notes: GDPpc (PPS) (GDP per capita in PPS); GVA Agri per Empl (GVA of agricultural sector by employment in agriculture); GVA Agri per AA (GVA of agricultural sector by agricultural area); Empl per AA (Employment in agricultural sector by agricultural area); GVA share Agri (Share of GVA of agriculture); GVA share of Ind (Share of GVA of industry); Pop dens (Population density); Birth rate (crude birth rate); Net migr (Net migration); EU TM (EU Trademark); CD (Community Design); Forest (Forest area percentage); Artif (Artificial area percentage); Agri (Agricultural area percentage); Mega1 (Distance to Mega 1 city); Mega2 (Distance to Mega 2 city); Mega3 (Distance to Mega 3 city); Mega4 (Distance to Mega 4 city).

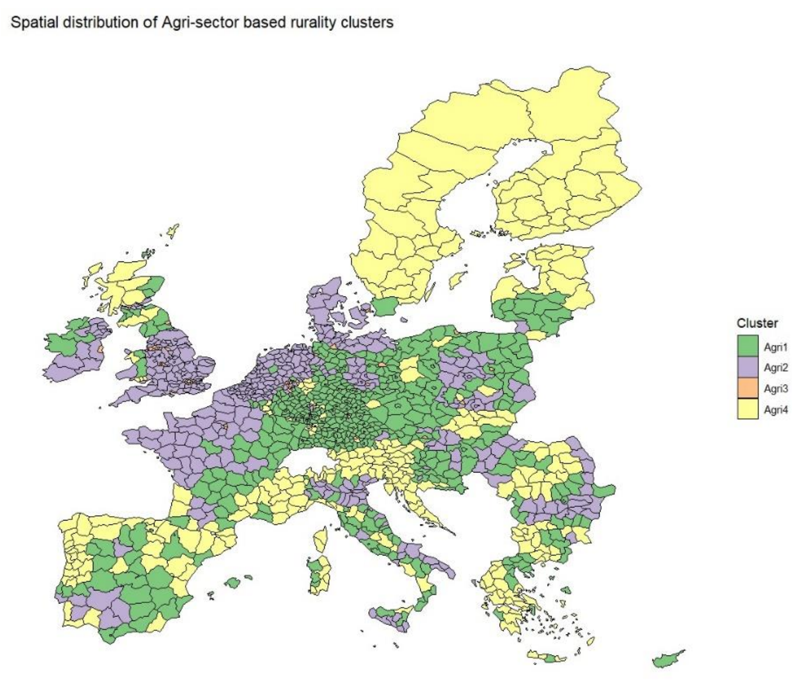
Table 2. Principal component loadings for the agricultural sector based approach

Variable	PC1	PC2	PC3	PC4
GVA Agri per Empl	-0.0245	0.2638	-0.6477	0.3754
GVA Agri per AA	0.3039	0.4707	-0.0583	0.5454
Emp Agri per AA	0.2834	0.1814	0.6348	0.1564
GVA share Agri	-0.0756	-0.3711	0.3066	0.6671
Forest	0.6035	-0.3573	-0.1676	-0.0444
Artificial	0.0494	0.639	0.2074	-0.2507
AA	-0.6741	0.0474	0.0949	0.1651

Notes: GVA Agri per Empl (GVA of agricultural sector by employment in agriculture); GVA Agri per AA (GVA of agricultural sector by agricultural area); Empl Agri per AA (Employment in agriculture by agricultural area); GVA share Agri (Share of GVA in agriculture);Forest (Forest area percentage); Artificial (Artificial area percentage); AA (Agricultural area percentage).

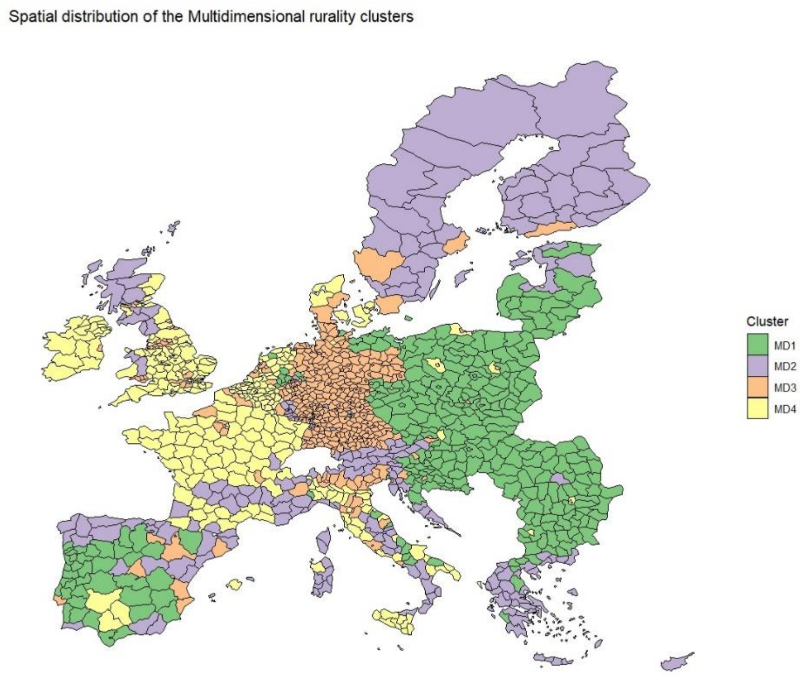
Below, Figure 1 and Figure 2 represent graphically Multidimensional clusters and Agri-sector based clusters.

Figure 1. Agri-sector based rurality clusters



Note: Agri sector based clusters. *Traditional low productivity agricultural sector (1), High labour productivity agriculture (2), Artificial areas with high productive land use (3) and Forest areas with low labour productivity (4).*
Source: author's calculation.

Figure 2 Multidimensional rurality clusters



Note: multidimensional clusters. *Depleting regions with mixed economies (1), Attractive forested regions with low agricultural productivity (2), Developed highly innovative semi-urban regions (3) and Semi-urban regions with large and developed agricultural areas and sector (4)*. Source: author's calculation.

The data are collected from several sources. The CAP funds are extracted from the European Commission *Clearance Audit Trial System* (CATS). This dataset is made available by DG AGRI and contains all payments to CAP beneficiaries at NUTS3 level divided by Pillar 1 instruments and Pillar 2 measures. The socio-economic variables, the outcomes and the GVA measures are collected from *Annual Regional Database of the European Commission* (ARDECO) provided by DG Regio and from the Eurostat regional database. The land-use variables are collected from CORINE Land Cover and EPSON databases.

5. Identification strategy

5.1 The CAP as multivalued treatment

The aim of this paper is to evaluate the causal impact of the CAP on socioeconomic outcomes. In this context, the CAP is considered as a discrete multivalued treatment instead of a continuous treatment. This process can be disentangled in different steps. First of all, each region is characterized by own policy mixes composed of different level of Direct Payments, Market Measures and Rural Development funds. This disaggregation of CAP funds is effective to characterize CAP's multidimensionality. Then, regions' CAP mixes are clustered to produce a multivalued treatment in order to design a set of policy implementation. This approach is fundamental to simplify a continuous multivariate treatment and, at the same time, it does not neglect the composition of the treatment levels which is a common drawback in the existing empirical studies regarding CAP impact evaluation. Allowing for heterogeneity within each treatment level makes the impact analysis feasible, as different units under the same treatment can be grouped.

Three main issues arise in estimating the CAP's causal impact: the characterisation of the determinants of the treatment allocation, the absence of a control group and the identification of CAP as a policy mix.

Firstly, in analysing the CAP, the main problem is that the "treatment" is not randomly assigned (Montezuma et al., 2021). In the case of randomly assignment to the regions, the impact would be estimated by simply comparing the average outcomes with different treatments. Another alternative that provides causal results could be that all regions are similar or that the CAP mix choices are independent from regions' characteristics. However, indeed, the abovementioned situations are hypothetical. Actually, distribution of CAP payments are driven by regional features. Pillar 1 funds are related to farming sector aspects, while Pillar 2 funds are determined by socio-economic regions' design. Therefore, defining regional differences that justify CAP implementation decisions is a fundamental step for the identification strategy to establish the causal effect. In fact, if all treatment's determinants are taken into account, then the randomisation condition is re-established and the treatment is independent from the potential outcome. Under this *selection-on-observables assumption*, the causal impact of the CAP can be estimated (Montezuma et al., 2021). Therefore, the first step is to identify and measure the pre-treatment variables on which treatment is based on.

The second obstacle in analysing the CAP causal impact lies in the absence of a control group. Generally, CIE methods are based on the comparison between the outcomes of units that receive the treatment and non-treated units which constitutes the counterfactual scenario. In the case of the CAP, all units (NUTS3 regions) can be beneficiaries and this does not permit to identify a control group that allows to build a counterfactual. Thus, the proposed model goes beyond the simple logic of binary dichotomy (treated/non-treated) and builds the control group exploiting different intensities and composition of the CAP funds. To sum up, the causal effect is identified comparing the effects that emerge varying the policy mix.

Finally, the third point that has to be clarified is the definition of multivalued treatment. In this study, the multidimensional aspect of the treatment is preserved as multivariate continuous CAP treatment is expressed by a discrete policy mix vector that describes the regions' implementation choices (Montezuma et al., 2021). This simplification allows to diminish the dimension of the treatment and, at the same time, maintains the qualitative aspect associated with the different mixes, actually considering the CAP policy as a whole.

5.2 Cluster Analysis and creation of treatment level groups

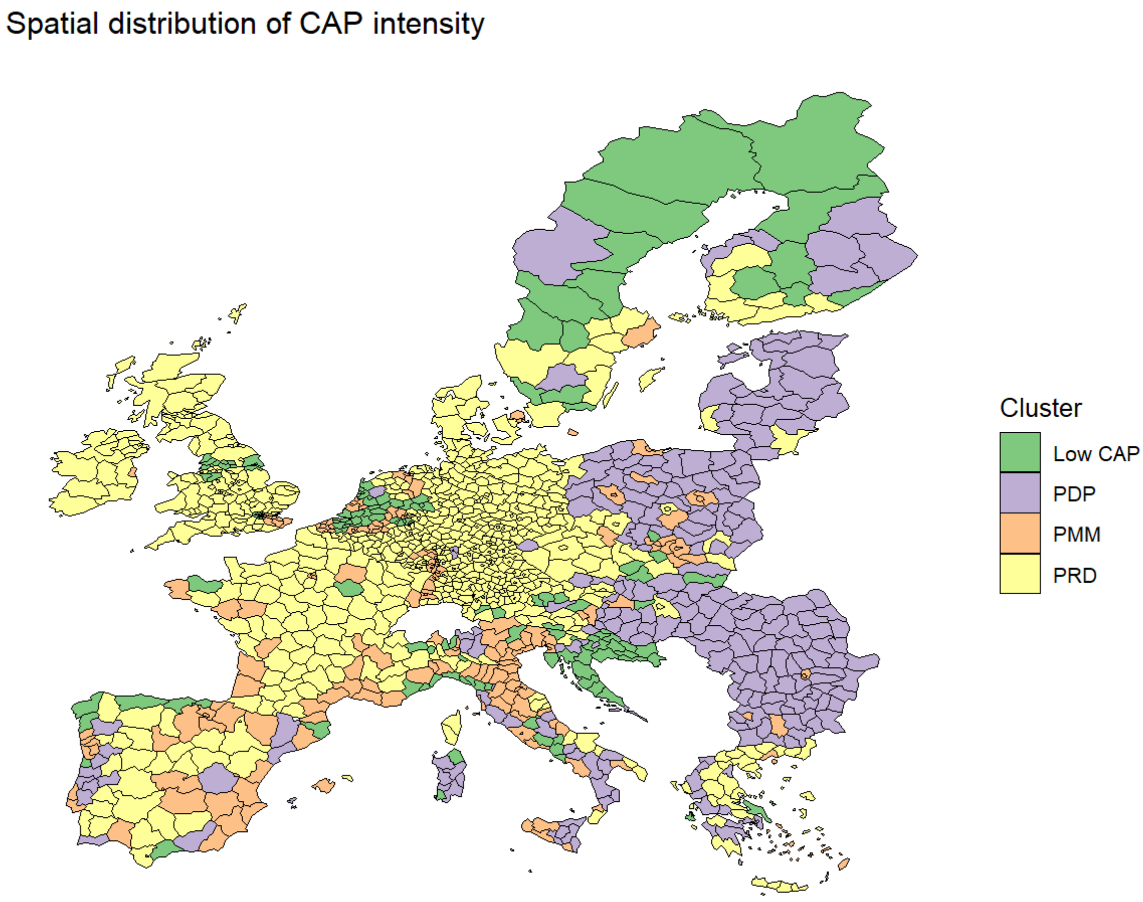
As it is shown in Section 2, since the 90s many reforms have affected the CAP. In particular, the 2003 Fischler reform introduces two distinct funds to finance the policy: the European Agricultural Guarantee Fund (EAGF) and the European Agricultural Fund for Rural Development (EAFRD). The former finances direct payments to farmers and measures to respond to private or public storage and to stabilize market prices. Whereas, the latter finances the Member States (MS) rural development programmes. The CAP structure suggests that it is possible to consider the CAP as a policy mix choices addressed to single MS, Managing Authorities (MA) and farmers.

This analysis looks at the spatial distribution of CAP funds that characterises EU-28 European NUTS3 regions across the period 2011-2015. This characterization is the result of a cluster analysis based on specific instruments and measures of Pillar 1 and Pillar 2 (Direct Payments, Market Measures and Pillar 2 as a whole). The fundamental step that needs to be accurately taken is to specify economic and geographical context which could explain the CAP expenditure profile of each NUTS3 region. Cluster analysis generates four groups that correspond to the four CAP policy mixes (*Low CAP*, *Predominantly Market Measures*, *Predominantly Direct Payments* and *Predominantly Rural Development*) taken into account.

In this analysis, CAP funds are considered as intensities in order to make comparisons across regions and identify their relevance both for regional economy and for agricultural sector, which constitutes the primary beneficiary of Pillar 1 direct payments.

As previously mentioned, all EU regions can be potentially beneficiaries. For this reason, the first step of this analysis is to identify a baseline treatment group that reproduces as close as possible a control group with low intensity in all considered CAP funds. In this case, the *Low CAP* group is composed of 100 regions with simultaneously all treatment level of Pillar 1 and Pillar 2 below respectively the fifth and sixth decile. The subsequent step is grouping the remaining regions using a hierarchical cluster algorithm on the three types of funds. Cluster analysis is the appropriate statistical tool in this case as units in the same cluster are more similar than unit in other clusters (Hastie et al., 2009). Beyond the baseline cluster, other three clusters are identified which receive different intensities of Direct Payments, Market Measures and Rural Development funds. Figure 3 represents graphically NUTS3 regions distribution of the four CAP intensities.

Figure 3. Spatial distribution of CAP mixes



Note: spatial distribution of the four CAP mixes *Low CAP*, *Predominantly Direct Payments (PDP)*, *Predominantly Market Measures (PMM)* and *Predominantly Rural Development (PRD)* across the European Union – 28.

5.3 The Generalized Propensity Score

In the setting previously described (lack of randomly assigned treatment), the most suitable method for inferring causality is the Generalized Propensity Score (GPS) because it provides a strategy to delete the selection bias. This method allows to isolate the effect of the policy from the regional characteristics (the cofounders) controlling for all determinants of treatment levels. The fundamental assumption is that the pre-treatment features conditioning both funds' allocations and the potential outcomes can be observed.

Imbens (2000) extends Rosenbaum and Rubin's work (1983) for the binary treatment to the discrete multivalued treatments by computing for each region the probability of implementing each CAP mix as a function of their characteristics (Montezuma et al., 2021). Since the probability to be treated (the GPS) is known under certain assumption, the intuition behind this methodology is that, firstly, it deletes the influence of pre-treatment differences on the treatment assignment and, secondly, it is able to estimate the Expected Potential Outcomes (EPO) for all treatment levels. The EPO describes the average outcome that a potential region would obtain under a certain level of treatment. The difference between two Expected Potential Outcomes will provide the Average Treatment Effect (ATE) under two different treatment levels.

$$ATE_{l,m} = EPO_l - EPO_m = E[Y_i(l)] - E[Y_i(m)] \quad l \neq m \in \tau \tag{1}$$

More formally, let $T_i \in \mathrm{T}, \mathrm{T} = \{1, \dots, t)$ denote the treatment assignment of region i, t the possible CAP mix and X_i the vector of observed pre-treatment covariates (Agri cluster and Multidimensional cluster). Let Y_i be the observed outcome of the region i which depends on X_i and $Y_i(t)$, the potential outcome, associated with the treatment t. The observed outcome can be expressed as:

$$Y_i = \sum_{t=1}^{T} Y_i(t) I(T_i = t) \tag{2}$$

where $I(T_i = t)$ is the indicator of receiving the treatment t. Let note that only potential outcome is observable, being all other counterfactuals.

The purpose is to estimate the unobserved potential outcome of a region i through the observed outcome of the units in the opposite status but with similar characteristics. Therefore, treatment effect and average treatment effect are calculated as follows:

$$TE_{i,t\kappa} = Y_i(t) - Y_i(k) \tag{3}$$

$$ATE_{t,k} = E\{Y_i(t)\} - E\{Y_i(k)\} \tag{4}$$

In non-experimental settings like the current one, since the treatment status is correlated with the pre-treatment covariates, the difference among observed sample means across groups with different treatment levels is a biased estimator of the ATE.

In this framework, Imbens (2000) defines the generalized propensity score $r(t,\ X_i)$ as the conditional probability of receiving treatment level t given the pre-treatment variables X_i,

$$r(t, X_i) = p(T_i = t | X_i = X_i) \tag{5}$$

Two fundamental assumptions have to hold to apply GPS: weak unconfoundedness and overlapping. The former assumption means that the treatment assignment T_i must be weakly unconfounded given the observed covariates X_i, that means the potential outcome is independent from the treatment level, given the covariates:

$$\mathrm{Y_i(t) \perp T_i = t | X_i} \tag{6}$$

The latter key assumption is the overlapping which claims that the probability to be treated is included in the interval 0-1:

$$0 < \mathrm{p}(T_i = \mathrm{t}|X_i) < 1\ ,\ \forall i, t \tag{7}$$

Formally, the next step consists in estimating the conditional expected outcome for unit i under treatment t, given the GPS $r(t, X_i)$:

$$\beta(t, r_i) = E\{Y_i(t) | r(t, X_i) = r_i\} = E\{Y_i | T_i = t, r(t, X_i) = r_i\} \tag{8}$$

The last step is to estimate the dose-response function to a specific level of treatment t averaging the conditional expectation of the outcome on GPS at that specific level of treatment t:

$$\mu(t) = E\{Yi(t)\} = E\big[\beta\big(t, r(t, X)\big)\big] \tag{9}$$

Given the GPS, many methods exist to estimate the expected potential outcome. In this work, the propensity score weighting approach is adopted, specifically the Weighted Least Squares regression estimator (Robins et al., 2000), as a variant of the Horvitz-Thompson (1952). It estimates the expected outcome as the average of individual potential outcome weighted by the inverse of the propensity score:

$$\hat{E}\{Y_i(t)\} = \sum_{i=1}^{N} \frac{Y_i(t)I(T_i = t)}{r(t, X_i)} \tag{10}$$

The key step is to well-specify the GPS because the independence between the potential outcome and the treatment that arises from the uncounfoundedness assumption is achieved conditioning on it. Practically, if the conditional independence is guaranteed conditioning on GPS, then the pre-treatment variables will be balanced across the different treatment clusters. By contrast, if after the conditioning, treatment groups still depend on treatment, that implies a misspecification of the GPS or a fall in the assumption. A proper specification depends on the choice of treatment conditional distribution, specifically on the set of conditioning variables. However, balancing the covariates is a difficult task. To solve this issue, in this analysis the Covariate Balancing Propensity Score (CBPS) by Imai and Ratkovic (2014) is adopted. The CBPS models treatment assignment while optimizing the covariate balance. The CBPS exploits the two fundamental properties of the propensity score: covariates balancing and the conditional probability to be treated. The estimation of the CBPS is done within the generalized method-of-moments. The authors show that the CBPS improves methods based on the propensity score specification.

6. Results

The estimation of the causal effect of the CAP follows three main steps. Firstly, the CBPS is computed conditioning on the pre-treatment variables. The estimates are derived from a general method of moments (GMM) based on logistic regression. Secondly, the overlapping assumption, the distribution and the balancing proprieties of the GPS are assessed (Imbens and Rubin, 2015) and the weights are computed as the inverse of the probability scores. Thirdly, the EPOs and the ATEs (with respect to the Low CAP group) of the remaining treatment levels are computed by Weighted Least Squares Regressions (Robins et al., 2000; Freedman and Berk, 2008).

First of all, properties of casual estimates derived from CBPS procedure have to be investigated. As mentioned before, holding of weak unconfoundedness assumption allows the estimates of EPOs and ATEs which entails that, correctly specifying the GPS, the pre-treatment variables are balanced across treatment levels. For doing this, the CBPS package (Fong et al., 2021) estimates the GPS jointly with a moment condition that implies this balancing. The R package (R Core Team, 2022) is used to estimate the GPS specification and the covariate balancing checks are run using the R package cobalt (Greifer, 2022).

Table 3 shows the CBPS estimates of the GPS on the categorical variables which represent the *Multidimensional* and *Agricultural* sector-based clusters. The bottom row reports the Hansen's J-statistics for the test of overidentifying restrictions. The test statistics are close to 0 which implies the GPS's correct specification.

Table 2. CBPS estimates

	$P(T_i=1)$			$P(T_i=2)$			$P(T_i=3)$		
	Estimate		t-stat	Estimate		t-stat	Estimate		t-stat
(Intercept)	1	***	4.74	1.41	***	8.02	0.442	*	2.47
	(0.212)			(0.175)			(0.179)		
Agri_CL2	-1.17	***	-12.1	-1.4	***	-15.9	-0.725	***	-6.39
	(0.0963)			(0.0878)			(0.113)		
Agri_CL3	0.526	***	4.74	0.287	***	3.64	0.305	***	3.68
	(0.111)			(0.0788)			(0.0829)		
Agri_CL4	0.159	.	1.81	-0.169	*	-2.4	0.0215		0.285
	(0.0876)			(0.0706)			(0.0753)		
MD_CL2	-0.67	***	-6.97	-0.185	.	-1.92	-0.43	***	-3.8
	(0.0961)			(0.0963)			(0.113)		
MD_CL3	-0.492	***	-4.46	-0.0517		-0.514	0.00464		0.0413
	(0.11)			(0.101)			(0.112)		
MD_CL4	-0.905	***	-9.83	0.281	***	3.54	-0.788	***	-6.84
	(0.092)			(0.0794)			(0.115)		
j-statistic:	0.013199				Note:	*p<0.1;	**p<0.05;	***p<0.01	

Note: T_i (CAP clusters); Agri_CL: Agri sector-based clusters; MD_CL: Multidimensional clusters.

As previously mentioned, the successive step is to verify the overlapping assumption, the distribution and the balancing properties of the GPS. Table 4 reports the maximum absolute mean difference between the covariates observed across all pairs of treatment levels. Values are all below the standard threshold of 0.10 which implies a large imbalance across pairwise comparisons.

Table 3. Maximum adjusted difference across contrast by control variable

Balance summary across all treatment pairs

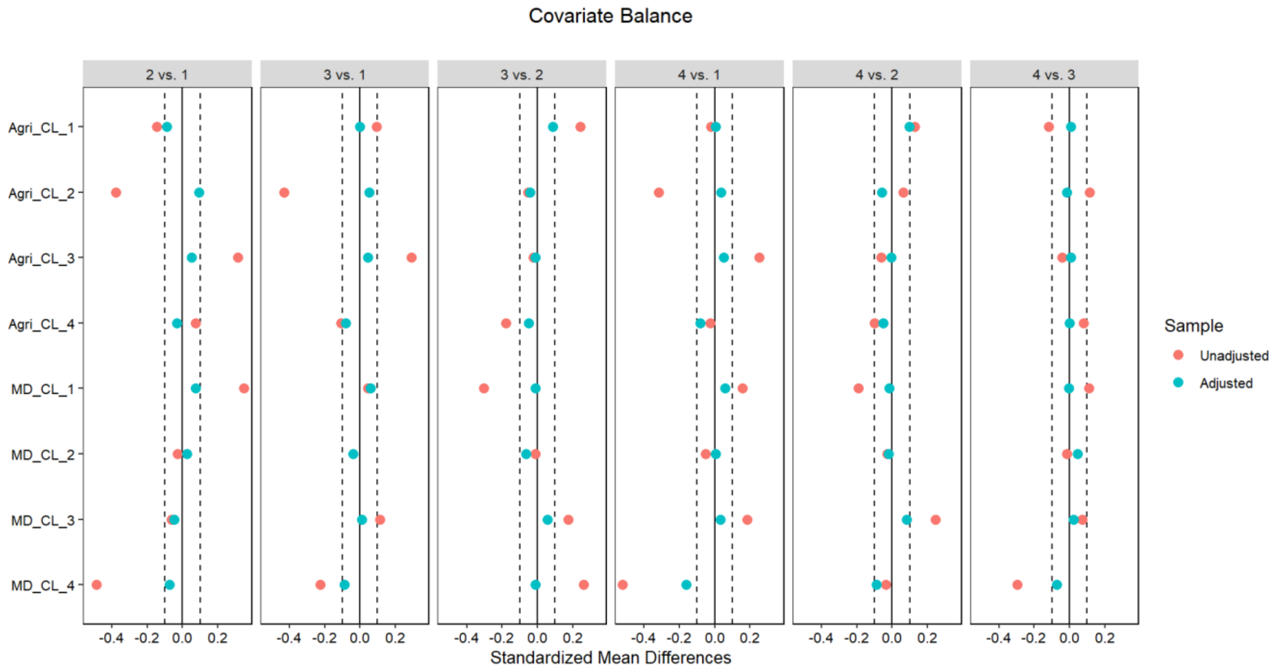
	Type	Max.Diff.Adj
Agri_CL_1	Binary	0.042
Agri_CL_2	Binary	0.029
Agri_CL_3	Binary	0.025
Agri_CL_4	Binary	0.037
MD_CL_1	Binary	0.0364
MD_CL_2	Binary	0.0169
MD_CL_3	Binary	0.0373
MD_CL_4	Binary	0.0455

Note: table reports the maximum mean difference between the covariates observed across all pairs of treatment levels. Agri_CL: Agri sector-based clusters [*Traditional low productivity agricultural sector (1), High labour productivity agriculture (2), Artificial areas with high productive land use (3) and Forest areas with low labour productivity (4)*]. MD_CL: Multidimensional clusters [*Depleting regions with mixed economies (1), Attractive forested regions with low agricultural productivity (2), Developed highly innovative semi-urban regions (3) and Semi-urban regions with large and developed agricultural areas and sector (4)*]. Source: author's calculation.

In the shed of abovementioned imbalance reported in Table 4, the next step must be the balancing of the covariates. Figure 4 is a *Love Plot* which is a graphic representation of the Standardized Mean Differences of the covariates across treatment levels[13]. In this case, this tool is adopted to make pairwise comparisons among the treatment levels. This figure provides evidence of the reduction in unbalancing after the propensity score adjustments.

[13] Blue bullets represent the adjusted differences, whereas red bullets represent the unadjusted ones.

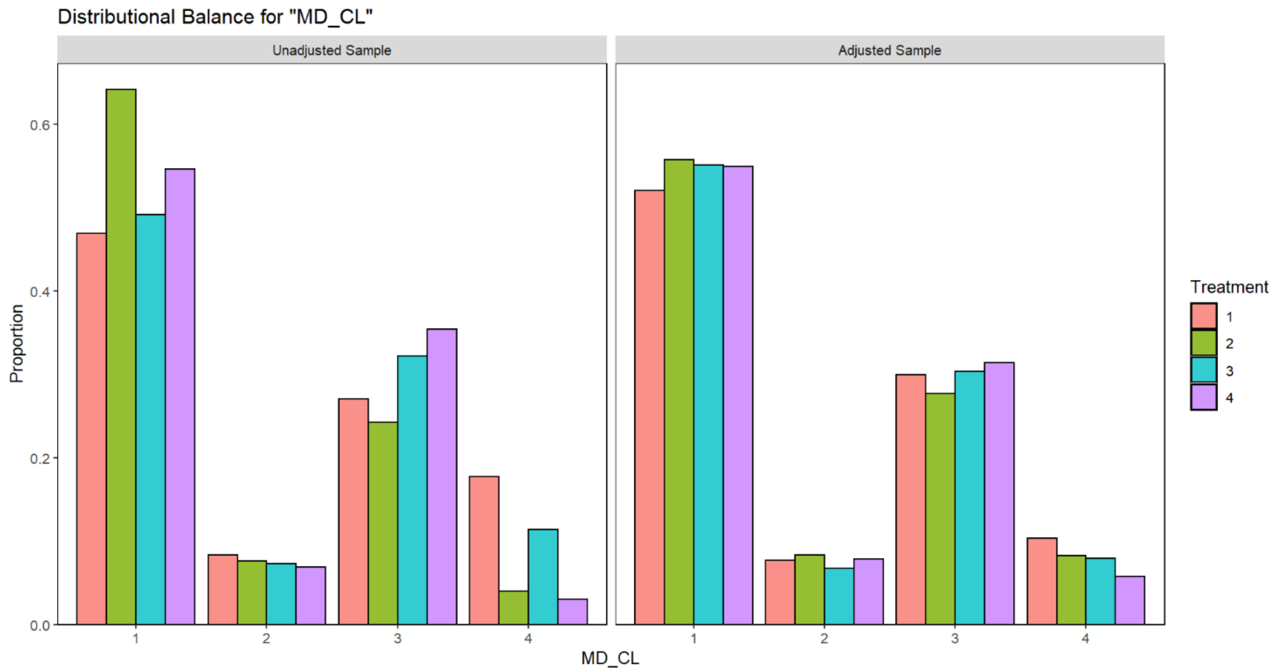
Figure 4. Love plots representing pairwise covariate balance by contrast of treatment levels



Note: Agri_CL: Agri sector-based clusters *[Traditional low productivity agricultural sector (1), High labour productivity agriculture (2), Artificial areas with high productive land use (3) and Forest areas with low labour productivity (4)]*. MD_CL: Multidimensional clusters *[Depleting regions with mixed economies (1), Attractive forested regions with low agricultural productivity (2), Developed highly innovative semi-urban regions (3) and Semi-urban regions with large and developed agricultural areas and sector (4)*]. Source: author's calculation.

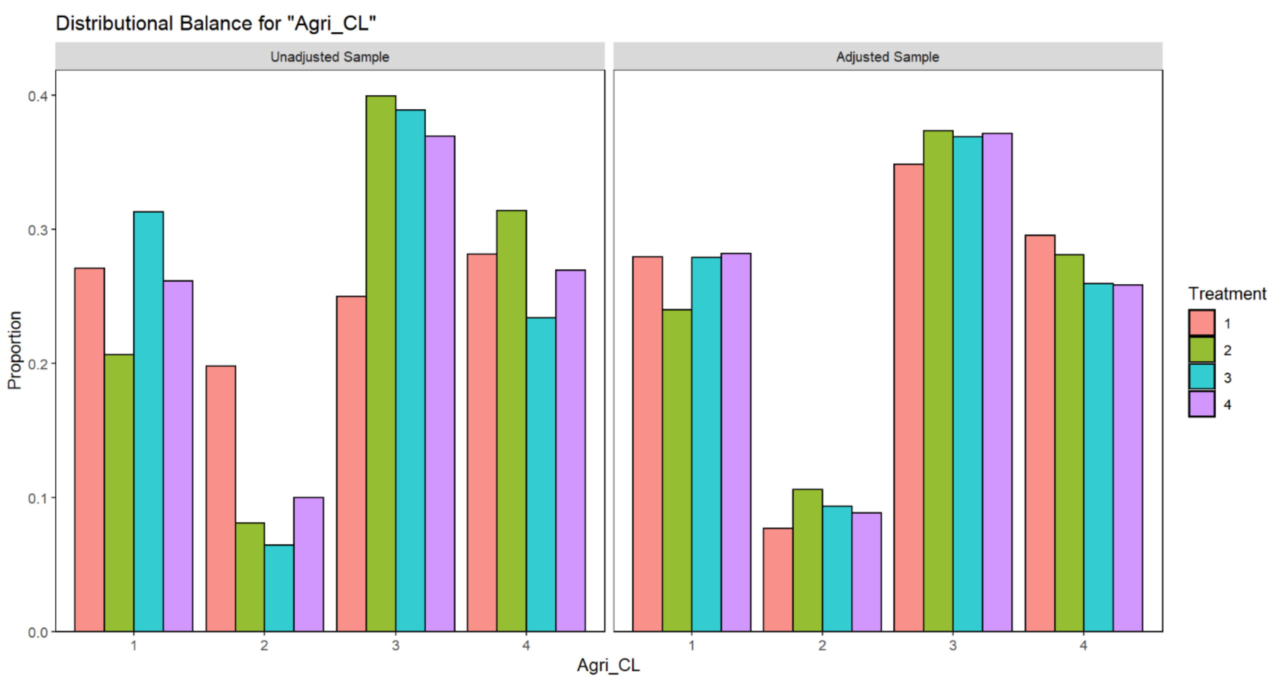
Furthermore, Figures 5 and 6 show the balance check for Multidimensional and Agricultural clusters by treatment levels. On the left and on the right panels, respectively, the distribution is represented before and after the propensity score adjustment. Generally, these graphs display distributional balance for the covariate taken into account across all treatment groups.

Figure 5: Balance check for Multidimensional cluster



Note: distributional balance for multidimensional clusters. *Depleting regions with mixed economies (1), Attractive forested regions with low agricultural productivity (2), Developed highly innovative semi-urban regions (3) and Semi-urban regions with large and developed agricultural areas and sector (4)*. Source: author’s calculation.

Figure 6: Balance check for Agricultural cluster



Note: distributional balance for agri sector based clusters *[Traditional low productivity agricultural sector (1), High labour productivity agriculture (2), Artificial areas with high productive land use (3) and Forest areas with low labour productivity (4)*]. Source: author's calculation.

Finally, the last part of the analysis consists properly in evaluating the effect of the CAP policy mixes in the three years after the implementation. In fact, considering the growth rates between 2010 (a year before the implementation) and the three years after is functioning to capture time persistent and provides a robustness check for the analysis.

Tables 5 and Table 6 report the EPOs and the ATEs, respectively. The EPOs measure the expected outcomes under each policy mix after controlling for the pre-treatment regional differences. They are computed respectively one, two and three years after the policy implementation to capture the temporal dynamics of the CAP impact. Whereas, the ATEs measure the average effect of each CAP mix relative to the Low CAP mix calculated as the difference between the EPOs. The columns show the results for the population of NUTS3 regions for the three outcomes[14] (*GDP per capita*, *GVA in Agriculture* and *Employment in Agriculture*) under the four CAP policy mixes (*Low CAP*, *Predominantly Direct Payments*, *Predominantly Market Measures* and *Predominantly Rural Development*).

Table 5 show the expected potential outcomes under each policy mix. As far as GDP is concerned, results are statistically significant under all treatments. However, except for PDP treatment, all the reported coefficients are negative. This implies that in the NUTS3 regions where CAP funds are chiefly invested in direct payments, the expected growth is positive and increasing over the period under analysis. Whereas, the others policy mixes provide a progressively decreasing in GDP growth. Surprisingly, the expected growth in agricultural productivity is significant only in those regions that implement a policy characterized by a low investment in CAP funds. However, it is coherent as the coefficient is negative which means that regions that implement a policy of Low CAP record a decrease in the gross value added from agricultural activities. Finally, with respect to employment in agriculture, all coefficients are strongly significant (at 1% level), even if they

[14] The analysis has been replicated taking into account two-year average of agricultural outcomes. This necessity arises from the inherent natural variability in agricultural production, making a single-year measure of output potentially misleading. However, the results exhibit minimal changes, leading to the decision not to include them here to avoid redundancy. This could be attributed to the relatively negligible variability observed across the years considered in this study to calculate the growth rate. Results are available upon request.

are all negative. This suggests that, regardless the implemented CAP policy mix, all NUTS3 regions will record a diminishing growth in agricultural work force.

Overall, after isolating the regional differences and given the current economic environment, *Predominantly Direct Payment* mix produces over time a significant result. However, only as far as the expected growth in GDP is concerned, it is increasing. On the other hand, the other policy mixes determine a statistically significant and decreasing awaited growth in all outcomes of interest, especially in the primary sector ones.

Table 4. EPOs estimates for GDP, GVA and Employment

		GDP	**GVA**	**EMP**
Low CAP	t+1	-0.013**	-0.058***	-0.204***
		(0.006)	(0.015)	(0.012)
	t+2	-0.019***	-0.052***	-0.256***
		(0.007)	(0.016)	(0.012)
	t+3	-0.021***	-0.046**	-0.321***
		(0.008)	(0.020)	(0.020)
PDP	t+1	0.029***	-0.013	-0.216***
		(0.006)	(0.015)	(0.012)
	t+2	0.033***	-0.027	-0.287***
		(0.007)	(0.016)	(0.012)
	t+3	0.045***	-0.026	-0.370***
		(0.008)	(0.020)	(0.020)
PRD	t+1	-0.008	-0.011	-0.182***
		(0.006)	(0.015)	(0.012)
	t+2	-0.014**	-0.021	-0.218***
		(0.007)	(0.016)	(0.012)
	t+3	-0.019**	-0.019	-0.246***
		(0.008)	(0.020)	(0.020)
PMM	t+1	-0.014**	0.027*	-0.149***
		(0.006)	(0.015)	(0.012)
	t+2	-0.027***	-0.002	-0.196***
		(0.007)	(0.016)	(0.012)
	t+3	-0.038***	-0.015	-0.242***
		(0.008)	(0.020)	(0.020)

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Note: Expected Potential Outcomes (EPO) for the three outcomes Gross Domestic Product (GDP), Gross Value Added (GVA) in Agriculture and Employment in Agricultural sector (EMP) across the four policy mixes Low CAP, Predominantly Direct Payments (PDP), Predominantly Rural Development (PRD) and Predominantly Market Measures (PMM). The analysis is performed at time t+1 (2016), t+2 (2017), t+3 (2018) in order to capture time effect. *p<0.1; **p<0.05; ***p<0.01

Table 6 shows the Average Treatment Effects (ATEs) which means looking at the differential contribution of each policy mix in comparison to the baseline cluster (Low CAP). Concerning GDP, only *Predominantly Direct Payments* mix is statistically significant and increasing positive in comparison to the baseline treatment. This implies that the other two policy mixes (PMM and PRD) have a similar impact to *Low CAP* in terms of GDP. By contrast, in those regions that implement a policy characterized by a prevalent allocation of CAP funds in direct payments, it is recorded an increase in differential with the baseline that varies from 4.2% in 2016 to 6.6% in 2018. Therefore, it is possible to claim that direct subsidies to farmers produce a GDP growth in the abovementioned NUTS3 regions, but the same effect is not observed in those regions that mainly implement policies based on market measures and rural development. As far as agricultural productivity is concerned, all treatments have a positive and significant effect in 2016, reaching even an increment by 8.5% above the Low CAP treatment under PMM policy mix. However, GVA becomes not significant at time *t+2* except for those regions that implement a policy mix chiefly characterized by market measures (which, however, decrease to 5.1% with respect to the previous year). This discloses that, excluding in 2016, the impact on the three outcomes is similar to the baseline scenario. By contrast, in 2016, all the three treatments have a positive and significant effect with respect to *Low CAP*. Therefore, in those regions that attract a major amount of CAP funds (PDP, PMM and PRD) the gross value added in agriculture increases; however, the effect is not persistent along time. Finally, regarding the effect on agricultural employment, significant value are recorded for all the treatments. However, the coefficient are positive for PRD and PMM but negative for PDP. This means that in comparison to a policy characterized by a low level of CAP, all the three policy mixes cause an increment of agricultural employment contributing to safeguard jobs in the primary sector. In particular, those regions that invest more in market measures, the increase in agricultural employment rages from 5.5% in 2016 to 7.9% in 2018. Furthermore, regions that allocate fund to rural development measures, the rate of employment rises by a 7.5% in 2018. Surprisingly, regions that choose to invest mainly in direct payments observe a negative effect with respect to baseline setting in terms of job safeguarding.

Overall, looking at all the three outcomes, it is observed that regions that decide to allocate CAP funds show an advantage in comparison to the setting that present a low amount of investments. In particular, a policy that foster direct payments to farmers lead to an increase in GDP growth rates, while agricultural employment is mainly fostered by market measures investments. Moreover, a greater agricultural productivity is presented in all NUTS3 regions that implement all the CAP mixes.

Table 5. ATEs estimates for GDP, GVA and employment

		GDP	**GVA**	**EMP**
PDP	t+1	0.042***	0.046**	-0.011
		(0.008)	(0.022)	(0.016)
	t+2	0.052***	0.026	-0.031*
		(0.010)	(0.023)	(0.017)
	t+3	0.066***	0.020	-0.050*
		(0.011)	(0.028)	(0.028)
PRD	t+1	0.005	0.048**	0.023
		(0.008)	(0.022)	(0.016)
	t+2	0.005	0.031	0.038**
		(0.010)	(0.023)	(0.017)
	t+3	0.002	0.027	0.075***
		(0.011)	(0.028)	(0.028)
PMM	t+1	-0.001	0.085***	0.055***
		(0.008)	(0.022)	(0.016)
	t+2	-0.008	0.051**	0.059***
		(0.010)	(0.023)	(0.017)
	t+3	-0.017	0.031	0.079***
		(0.011)	(0.028)	(0.028)

Note: Average Treatment Effect (ATE) with respect to the baseline cluster Low CAP for the three outcomes Gross Domestic Product (GDP), Gross Value Added (GVA) in Agriculture and Employment in Agricultural sector (EMP) across the three policy mixes Predominantly Direct Payments (PDP), Predominantly Rural Development (PRD) and Predominantly Market Measures (PMM). The analysis is performed at time t+1 (2016), t+2 (2017), t+3 (2018) in order to capture time effect. *p<0.1; **p<0.05; ***p<0.01.

7. Conclusions

This study aims to estimate the Common Agricultural Policy's casual impact of the EU-28 NUTS3 regions' balanced territorial development. In the existing literature, most studies focus on single country or on single CAP instruments. Overtime, the CAP has evolved and many reforms are implemented, redefining its priorities. The initial goal of the CAP regards farmers' support and the maintenance of prices for agricultural producers and consumers in order to mitigate market distortions. Successively, the policy's aim progressively moves to a balanced territorial development.

This work contribution' consists in considering the CAP as a different policy mixes and in taking into consideration a new way to measure the convergence between rural and urban regions at NUTS3 level of disaggregation in the period 2011-2015. Furthermore, following Montezuma et al. (2021), this study proposes an innovative approach to investigate the CAP characterised by multiple interventions. The multivalued treatment is defined by clustering regions according to their policy mix, highlighting four types of policy mixes: Low Cap, Predominantly Direct Payments, Predominantly Market Measures and Predominantly Rural Development.

The impact of the multivalued discrete treatment variable is analysed using the Generalized Propensity Score (GPS) by Imbens (2000). Counterfactual impact evaluation methods allow to infer causality isolating the impact of the policy from the effects of the regional characteristics on the CAP policy implementation choices. The treatment is not randomly assigned, but it is linked to the socio-economic profile of each regions and to the outcomes. For this reason, it is crucial to define the set of pre-treatment variables that characterise the regions. This work computes two cluster analyses based on NUTS3 socio-economic indicators. These provide a Multidimensional clusters and an Agri sector-based clusters, considered immediately before the year of implementation, which describe the regional characteristics.

The results shed light on different CAP mixes impact on socio-economic outcomes and on the grade of convergence between rural and urban areas. Market measures and Rural Development measures contribute to safeguard agricultural jobs and foster agricultural productivity in the EU-28 regions. On the other hand, Direct Payments positively affect the GDP per capita.

Of course, in this evaluation exercise, the characterization is not fully achieved. However, the presented casual effect still has a significantly smaller bias than the one presented in studies which adopt non-causal techniques. This should foster the use of CIE methods to assess the impact of EU policies and provides insights for further researches. Furthermore, the study's aim is to verify the effectiveness of the CAP to rebalance territorial disparities across EU regions. This insight represents a crucial aspect as improvements in policy efficacy gives policy makers the right direction.

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Appendix

Description of pre-treatment variables

In this paragraph, variables that measure the regional differences are described in detail.

The successful determination of the causal impact of the Common Agricultural Policy (CAP) requires the observation and measurement of variables that affect both the outcomes and the choices regarding the CAP mix. As explained in Section 4, the economic profile of a region, particularly the characteristics of its agricultural sector, play a significant role in the allocation of funds, which in turn have an impact on relevant outcomes.

A useful approach to summarize the complex and diverse features within the context of the CAP is to employ the concept of rurality and classify regions based on the intensity and nature of their rural characteristics. There are numerous specific characteristics of a region that define rurality, encompassing various aspects such as physical and human capital resources, the quality of productive structures, economic agglomeration and specialization, the local labour market, and more. While quantifying these dimensions using economic variables is an option, it can be expensive and inefficient due to potential high correlations among them. On the other hand, relying solely on a simplistic classification like EUROSTAT's rural typology, which distinguishes regions as predominantly urban, intermediate, or predominantly rural based on population density, is inadequate.

The report by Dumangane et al. (2021), published by the Joint Research Centre (JRC), tackles this issue by introducing a measure able to describe regional characteristics that encompasses multiple dimensions of the European Union's NUTS3 regions, which are relevant in the context of the Common Agricultural Policy (CAP). The methodology employed in the report builds upon the cluster analysis approach used by Camaioni et al. (2014) to create a characterization of rurality at the NUTS3 level. Also in this case, the analysis proposes two approaches for classifying the regional features in NUTS3 regions: a *Multidimensional approach* and an *Agri-sector based approach*. Both approaches utilize the same methodology. Initially, the study employs Principal Component Analysis (PCA) on a set of indicators. This step involves extracting the Principal Components, which represent the underlying factors influencing rurality. Once the Principal

Components are obtained, standardized scores for the EU NUTS3 regions in the sample are calculated. Lastly, these scores are subjected to a Ward hierarchical cluster analysis, which groups the regions based on their similarity in terms of rurality.

In the *Multidimensional approach*, the classification of rurality is based on several indicators categorized into six areas. These areas are:

- *Agricultural sector*: Labour productivity in agriculture (ratio of agricultural GVA in million PPS to total employment in agriculture); Land productivity in agriculture (GVA agricultural sector in million PPS by agricultural area); Total number of people employed in agriculture per agricultural area.
- *Local economy*: Share (in total) of agricultural gross value added (GVA); Share (in total) of industry GVA (except construction) and GDP per capita.
- *Demographics*: Population density (persons per square kilometre); Crude birth rate (the ratio of the number of live births during the year to the average population in that year); Crude net migration rate (including statistical adjustment during the year to the average population in that year).
- *Innovation*: Total number of European Union trademark (EUTM) applications and Total number of Registered Community designs (RCD).
- *Land use and landscape*: Share of forest area; Share of land covered by artificial areas and Share of agricultural areas.
- *Remoteness*: Distance of NUTS 3 regions from MEGAs (Metropolitan Economic Growth Areas)[15].

In this case, four clusters are produced and labelled as follows: *Depleting regions with mixed economies*, *Attractive forested regions with low agricultural productivity*, *Developed highly innovative semi-urban regions* and *Semi-urban regions with large and developed agricultural areas and sector.*

Typology 1 is labelled as '*Depleting regions*' due to its distinctive characteristic, which is reflected by a significantly high average negative value for the variable of Net migration rate. These regions

[15] See ESPON 111, Potentials for polycentric development in Europe. https://www.espon.eu/sites/default/files/attachments/fr-1.1.1_revised-full_0.pdf

are characterized by a declining population as a result of substantial outmigration. The phenomenon of shrinking regions within the European Union (EU) appears to be concentrated primarily in the New Member States (NMS), particularly in Bulgaria and Romania.

NUTS3 regions in typology 2 (‘*Attractive forested regions with low agricultural productivity*’) are characterized by large forests and are based on traditional agricultural sector with low productivity. These economies are sited mainly in Greece, South Italy, and Northern Europe countries such as Norway.

Typology 3 (‘*Developed highly innovative semi-urban regions*’) is associated with high GDP per capita and a low share of Gross Value Added (GVA) from the agricultural sector. These regions are characterized by a dense population and exhibit strong performance in innovation indicators such as the European Innovation Scoreboard (EUTM) and Research and Development (RCD) expenditure. This typology predominantly describes NUTS3 regions located in Germany and North of Italy.

Finally, regions in Typology 4 are identified as ‘*Attractive semi-urban regions with large agricultural areas*’ and are mainly characterized by a high net migration level. Many regions in United Kingdom and Spain belong to this cluster.

In the *Agri-sector based approach*, the analysis is limited to *Agricultural sector* and *Land use and Landscape areas.* In this case, the derived clusters are:

Tipology 1 (‘*Traditional low productivity agricultural sector’*) groups together the NUTS3 regions that possess traditional and extensive agricultural sectors, characterized by low productivity in terms of both labour and land. These regions tend to maintain traditional farming practices and have relatively lower levels of efficiency and output compared to other clusters. The focus on large-scale agricultural activities in these regions may result in challenges related to low productivity, potentially indicating the need for improvements in farming techniques, technology adoption, and resource management to enhance productivity levels. Many regions in Eastern countries and some regions in central Europe belong to this cluster.

Typology 2 (‘*High labour productivity agriculture*’) comprises the highly productive agricultural regions, characterized by high levels of productivity in both labour and land utilization. These regions are typically more urbanized and industrialized compared to others within the European

Union (EU). Regions located in North France, Belgium, North of Italy, Netherlands, and the UK are included in this category. These regions have demonstrated a capacity for efficient and effective agricultural practices, resulting in significant output and productivity levels. Their relatively more urbanized and industrialized nature indicates a higher degree of economic diversification and integration within broader regional economies.

Typology 3 (‘*Artificial areas with high productive land use*’) primarily encompasses artificial areas with a notable feature of highly productive utilization of small agricultural lands. These regions demonstrate efficient and effective agricultural practices despite the relatively limited size of their agricultural areas. The share of Gross Value Added (GVA) derived from agriculture in these regions is above the overall average, suggesting that agriculture contributes significantly to the region's overall economic output. In this cluster, jus few NUTS3 regions are present and are concentrated in Germany and UK.

Finally, Typology 4 (‘*Forest areas with low labour productivity*’) includes the NUTS3 regions characterized by a relatively significant agricultural sector with a large number of employees, but low Gross Value Added (GVA) production. These regions also tend to have relatively large forest areas. In 2010, Cluster 4 is primarily concentrated in countries such as Southern France, Norway and Croatia.

Below, tables with descriptive statistics for variables used both for Multidimensional and Agri-sector approach are reported.

Table A1: Descriptive Statistics Variables Multidimensional approach

Variables	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
GDP per capita in PPS	797	21471.8	9602.52	5581.77	148598.30
GVA Agri per Emp	797	24.03	15.52	1.03	104.79
GVA Agri per AA	797	0.13	0.17	0.00	2.65
Emp Agri per AA	797	0.01	0.01	0.00	0.11
Share of GVA of agriculture	797	0.04	0.04	0.00	0.23
Share of GVA of industry	797	0.22	0.10	0.01	0.62
Population density	797	325.61	888.55	1.86	11846.52
Birth rate (crude birth rate)	797	10.00	1.85	5.80	17.59
Net migration	797	0.88	5.16	-26.07	25.61
EU TM	797	82.84	208.65	0.00	2892.00
CD	797	68.75	173.40	0.00	2766.00
Forest (Forest area percentage)	797	39.19	21.76	0.00	91.12
Art (Artificial area percentage)	797	7.84	10.66	0.28	99.94
AA (Agricultural area percentage)	797	50.56	20.76	0.00	91.54
MEGA1	797	367.54	283.12	1.81	1955.33
MEGA2	797	560.07	310.40	5.74	1545.64
MEGA3	797	295.46	251.63	7.13	1781.38
MEGA4	797	264.67	161.91	1.91	1206.11

Notes: GDPpc (PPS) (GDP per capita in PPS); GVA Agri per Empl (GVA of agricultural sector by employment in agriculture); GVA Agri per AA (GVA of agricultural sector by agricultural area); Empl per AA (Employment in agricultural sector by agricultural area); GVA share Agri (Share of GVA of agriculture); GVA share of Ind (Share of GVA of industry); Population density (Population density); Birth rate (crude birth rate); Net migration (Crude rate of net migration); EU TM (European trademark applications); CD (Registered community designs); Forest (Forest area percentage); Art (Artificial area percentage); Agri (Agricultural area percentage); Mega1 (Distance to Mega 1 city); Mega2 (Distance to Mega 2 city); Mega3 (Distance to Mega 3 city); Mega4 (Distance to Mega 4 city).

Table A2: Descriptive Statistics Variables Agri-sector based approach

Variables	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
GVA Agri per Emp	797	24.03	15.52	1.03	104.79
GVA Agri per AA	797	0.13	0.17	0.00	2.65
Emp Agri per AA	797	0.01	0.01	0.00	0.11
Share of GVA of agriculture	797	0.04	0.04	0.00	0.23
Forest (Forest area percentage)	797	39.19	21.76	0.00	91.12
Art (Artificial area percentage)	797	7.84	10.66	0.28	99.94
AA (Agricultural area percentage)	797	50.56	20.76	0.00	91.54

Notes: GVA Agri per Empl (GVA of agricultural sector by employment in agriculture); GVA Agri per AA (GVA of agricultural sector by agricultural area); Empl Agri per AA (Employment in agriculture by agricultural area); GVA share Agri (Share of GVA in agriculture); Forest (Forest area percentage); Art (Artificial area percentage); AA (Agricultural area percentage).

Tables present an index of the average amount of funds in each cluster. The palette of colours varies from dark green (the maximum value) to red (minimum value of the index) with faint colours (and intermediate values).

Table A3: Heat table for Multidimensional clusters 2011-2015

	Local Economy			Agri-Sector			Demographics			Innovation		Land Use			Remoteness			
Multidimensional clusters	GVA share Agriculture	GVA share Industry	GDP pc (PPS)	GVA Agri per Empl Agri	GVA Agri per AA	Emp Agri per AA	Pop density	Birth rate	Net migration	EU trademark	Community Design	Forest	Artificial	Agriculture	MEGA1	MEGA2	MEGA3	MEGA4
Depleting regions with mixed economies																		
Attractive forested regions with low agricultural productivity																		
Developed highly innovative semi-urban regions																		
Semi-urban regions with large and developed agricultural areas and sector																		

Notes: GDPpc (PPS) (GDP per capita in PPS); GVA Agri per Empl (GVA of agricultural sector by employment in agriculture); GVA Agri per AA (GVA of agricultural sector by agricultural area); Empl per AA (Employment in agricultural sector by agricultural area); GVA share Agri (Share of GVA of agriculture); GVA share of Ind (Share of GVA of industry); Pop dens (Population density); Net migr (Net migration); EU TM (EU Trademark); CD (Community Design); Forest (Forest area percentage); Artif (Artificial area percentage); Agri (Agricultural area percentage); Mega1 (Distance to Mega 1 city); Mega2 (Distance to Mega 2 city); Mega3 (Distance to Mega 3 city); Mega4 (Distance to Mega 4 city).

Table A4: Heat table for Agri-sector based clusters 2011-2015

	Agricultural Sector						
Agri-sector based clusters	GVA Agri per Empl Agri	GVA Agri per AA	Emp Agri per AA	GVA Share Agri	Forest	Artificial	Agriculture
Traditional low productivity agricultural sector							
High labour productivity agricolture							
Artificial areas with high productive land use							
Forest areas with low labour productivity							

Notes: GVA Agri per Empl (GVA of agricultural sector by employment in agriculture); GVA Agri per AA (GVA of agricultural sector by agricultural area); Emp Agri per AA (Employment in agricultural sector by agricultural area); GVA share Agri (Share of GVA of agriculture); Forest (%) (Forest area percentage); Artificial (%) (Artificial area percentage); Agriculture (%) (Agricultural area percentage)

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CHAPTER 3

Gender bias at a glance: does toponymy matter? Some considerations on the Italian case[1]

[1] Co-authored with Gianluca Cerruti and Marta Santagata

Abstract

Streets names reflect the commemorative decisions of a community since they represent not only the historical and political causes of naming and renaming process that a city experiences, but also social and cultural values. Since history is written by winners, minorities are usually underrepresented in commemorative streets names. Women surely do not constitute a minority, but they are historically excluded from the public sphere and, consequently, they do not frequently appear in street names.

This study, exploiting street names as source of geographical and cultural data, aims to analyse individual perception towards gender equality through urban toponymy in Italian municipalities. Specifically, different specifications of a Probit model are estimated to observe how a change in the ratio of streets named after women is related to the probability of an individual to have a more equitable gender perception.

Results show that, even when controlling for a complete set of geographic, socio economic and historical controls, in the Italian municipalities with a higher percentage of streets named after female, there is more awareness about gender bias and a greater attitude towards gender equality, even if still far from parity.

1 Introduction

Modern political culture utilizes street names for commemorative aims and street names have a crucial role in building a shared past, beyond their primary function of spatial organizations of the cityscape (Azaryahu, 1996). Street names have a strong symbolic importance and the lack of specific categories' representation in street naming sounds like a synonym of social exclusion. As Gutierrez-Mora and Oto-Peralías (2022) note, it is not particular surprising that minorities are underrepresented in commemorative street names since the latter express the predominant socio-political order. Even though women surely do not constitute a minority, they are historically categorized as a marginalized group and are underrepresented in the public sphere. Therefore, the analysis of gender bias in place naming could lead to some interesting considerations on the role of women in our society. In this regard, the Italian case is emblematic and data about streets named after female are striking since among the 21 Italian provincial capitals, only 6.6% of streets is named after women and, excluding saints and blessed, the figure falls to 3.9%.[1,2]

Following Oto-Peralías (2018) and Gutierrez-Mora & Oto-Peralías (2022), this study exploits streets names as source of geographical cultural data and adopts text-analysis to investigate gender equality perceptions through urban toponymy at municipal level in Italy.

Overtime, the use of street names has seen an evolution of its interpretation. As Oto-Peralías (2018) points out, adopting commemorative street names linked to national personalities within cityscape is a recent phenomenon. In fact, even if urban toponymy associated with important public figures has existed since the ancient times, street names began to undertake political purposes after the French Revolution. This issue has attracted the attention of researchers and an important strand of literature has focused on the historical and political causes of streets' naming and renaming process (Gonzalez-Faraco and Murphy, 1997; Palonen, 2008; Tretter, 2011; Tucci et al., 2011; Drozdewski, 2014; Rusu, 2020; Fabiszak et al., 2021; Alvanides et al., 2021). Nowadays, as pointed out by Rose-Redwood et al. (2010), street names represent social, cultural and political heritage. Following this phenomenon, different authors have also analysed the relation between

[1] Data source: https://italy.mappingdiversity.eu/

[2] In the Italian administrative setting, provinces are NUTS-3 region, while NUTS-2 regions are called regions. From now on we use these terms interchangeably

street naming, social and cultural values, that is, among others, national identity (Oto-Peralías, 2017), religiosity (Oto-Peralías, 2018), and male predominance (McDowell, 2008; Forrest, 2018; Bigon & Zuvalinyenga, 2020; Yu, 2014; Gutierrez-Mora and Oto-Peralías, 2022).

This study aims at contributing to this last strand of literature by analysing the relation between the individual perception towards gender equality of young Italians (i.e. 3,034 individuals between 20 and 35 years surveyed in 2017) and the share of streets named after female in their municipality of residence.

In this analysis, different specifications of a Probit model are estimated where we assess how differences in the ratio of streets named after women is related to the probability of an individual to have a more equitable gender perception. To this end, we exploit information contained in the Italian Permanent Census of Population and Housing to calculate the number of females' named streets over the total number of streets in each municipality.

Following Oto-Peralías (2018), street names reflect socio-cultural values since street naming is strictly related to commemorative decisions which, in turn, mirror local collective commemorative priorities. Indeed, in Italy the naming of public places and traffic areas is attributed by law to the municipal council and, as a consequence, we truly believe that considering toponymy can be a key element in understanding a population's attitude towards gender equality.[3]

Results show that, even when controlling for a complete set of geographic, socio economic and historical controls, in the Italian municipalities with a higher percentage of streets named after female, there is more awareness about gender bias and a greater attitude towards gender equality, even if still far from parity. In particular, estimates suggest that one unit change in the measure of female streets (%) increases the probability of having a more equitable gender perception by 1.3-1.6%.

Furthermore, to validate the results, two robustness checks are performed. First, the model is estimated with an alternative outcome, i.e. *WomenManager*. The results are confirmed also with this outcome, but the marginal effect is smaller in comparison to that estimated with the main specification. Second, the main explanatory variable is transformed into a dummy variable, i.e.

[3] Law n. 118 of 13 June 1927 and Circular No. 18 of 29 September 1992.

Dummy_share. In this case, the results remain positive and significant with a higher marginal effect of having more streets named after female on individual perception towards gender equality.

Finally, a section is devoted to study possible existence of heterogeneous effects, dividing the sample according to certain individual and territorial features. Chiefly, information about both individuals and individuals' parents' educational attainment are exploited. It turns out that the relation between percentage of streets named after women and a more equitable gender equality perception is more evident for not-educated individuals and for individuals with not graduated parents. Secondly, the sample is split according to the population size, dividing between small and large cities and between rural and urban areas. Findings suggest that the correlation between gender perception and female streets names holds considering internal areas and smaller towns.

Our contribution to the literature is threefold. First, this study is the first to test and corroborate that also in Italy toponymy incorporate socio-cultural values. Indeed, to the best of our knowledge, this relation has been tested in a limited set of countries, e.g. Spain (Oto-Peralías, 2018; Gutierrez-Mora and Oto-Peralías, 2022), Great Britain (Oto-Peralías, 2017), United Stated (Tretter, 2011), but not in Italy. Second, since the literature on gender perception and place naming is not yet well established and, to the best of our knowledge, only in the seminal paper by Gutierrez-Mora and Oto-Peralías (2022) this relation is put under scrutiny, we believe that our study brings the valuable contribution of verifying the external validity of results found in other contexts. Third, our findings have been obtained in a sample that is, in some way, even more challenging since it is composed entirely of young people aged 20-35. Indeed, young people represent the part of population which mostly use social networks, undoubtedly a mean to decontextualize from the cultural setting. In this sense, we claim that, if the relation between the number of streets named after female and a positive perception of gender equality holds in our sample, our results strengthen the power of toponymy in evidencing the persistence of culture and values.

The rest of the paper is organized as follows. In Section 2, related literature is scrutinized. In Section 3, the Italian context is depicted, data are described, and the identification strategy is represented. Then, in Section 4, results are illustrated and, finally, Section 5 concludes.

2 Related literature

This paper can be ascribed to two different strands of literature. First, it relies on the works that concentrate on the political process and commemorating dimension that have involved a specific cityscape naming, i.e. place naming (Giraut and Houssay-Holzschuch, 2016).[4] In this study, the analysis of place naming is addressed focusing on street names into the socio-economic dimensions with a particular emphasis on gender gap. Indeed, the second literature on which this study relies on is that on perception towards gender equality.

The branch of literature concerning the analysis of place naming is quite rich as "the naming process shed light on power relations - how some social groups have the authority to name while other do not – and the selective way in which such relations reproduce the dominance of certain ideologies and identities over others" (Rose-Redwood et al. 2010, p. 462). In particular, Azaryahu (1996) highlights how modern political culture utilizes street names for commemorative aims and studies common procedures of the naming and renaming of streets. Finally, he concludes that naming and renaming streets represents the multitude of narratives that get involved in the creation of social reality. This logic is replicated in the common phenomenon of renaming streets according to political changes.

Those hypotheses have been, in some way, investigated by different studies carried out by social scientists and focused on several European countries.

For instance, an interesting work by Gonzalez-Faraco and Murphy (1997) sheds light on how political regimes in Spain modify the toponymy according to their values, transforming the relationship between institutions and inhabitants. During the Second Republic, street names aim to foster the educational agenda; then, the military dictatorship of Franco sets up toponymy to impose fascist symbolism and, finally, the socialist democracy operates in the sense of eliminating the onomastics of vanquishers and losers. In the same vein, the work of Palonen (2008) analyses the change of streets names in Budapest between 1985 and 2001. The author highlights that changes do not express a simple transition toward an agreed post-communist value system as political direction diverges overtime at different administrative levels (nation state, municipalities

[4] Giraut and Houssay-Holzschuch (2016) carry out an important distinction between the analysis of *street names* and the analysis of *place naming*. In the first case, studies mainly focus on the etymology and its origin.

and districts). Street names reshaping is also pointed out by Drozdewski (2014) who investigates changes in street names in Krakow during three different political powers (Nazi, Soviet and Polish) in five different periods (1934, 1943, 1964, 1985 and 1996). The author evidences how both Nazi and Soviet see own occupation and how all three types of government foster their influence to affirm political control by strengthening past examples and claim cultural hegemony in the cityscape.

In the wake of the abovementioned papers, recent studies adopt a quantitative approach to address the evolution of commemorative street names. For instance, Rusu (2020) investigates the post-socialist place naming in three Romanian cities (Brasov, Cluj-Napoca and Sibiu) through a logistic regression model which is able to identify the contribution of each factor to toponymic transformations. The author finds that both street name features (politicized designations directly related to the socialist regime) and topographic characteristics (geographical allocation and size) determine streets renaming process after the fall of socialism. In addition, Alvanides et al. (2021) present a longitudinal analysis of street names in Leipzig over 102 years (1916-2018), applying a GIS visualisation techniques and they find that the majority name changes occurs at the threshold of regime change. Finally, Fabiszak et al. (2021) aim at distinguishing ideological from non-ideological street renaming procedures through an analytic process of encoding street renaming in two cities, respectively in Germany and Poland. They illustrate that a different consideration about what is ideological and what it is not may influence the cityscape.

As far as Italy is concerned, only one case study is reported in the current literature, specifically concentrated only on a single town (Milan) and not on the entire country. Tucci et al. (2011), using GIS methodology, analyse street names in the city centre of Milan. The researchers aim to reconstruct all different pasts and ideologies that co-exist overtime within the cityscape, proposing a useful tool that constitutes a visual display of street networks.

As mentioned before, street names represent not only political heritage but also cultural and social values. For instance, Oto-Peralías (2018) uses the street names as source of cultural data for quantitative analysis in Spain. In particular, he focuses on an indicator of religiosity (i.e. the number of religious streets), finding a strong correlation with the cultural factor that captures population’s religious positions and a negative correlation with economic development at the local level. As already observed in Oto-Peralías (2017), similar correlations show up within different countries: in Scotland, for instance, people living in street whose names commemorate Great Britain are less likely to identify themselves exclusively in Scottish cultural values.

Considering street names' strong symbolic importance, the lack of specific categories' representation sounds like a synonym of social exclusion. As Berg and Kearns (1996) note, "*naming* is a form of *norming*": they observe that place-names are the product of hegemonic groups who impose their social norms in Otago (New Zealand). Specifically, in that zone, place-names seem to be the legitimation of masculinist colonialism and colonial history which is translated in hegemonic arguments about gender, race and class. Another clear example of how commemorative place-naming reflects social patterns is described in Tretter (2011). The researcher highlights the disparity between white and African-American commemoration figures: "black commemorations" remain a "black thing". This means that these important figures still represent a symbol only for a part of sociocultural geography of the United States and tells us the limits of social inclusion which still characterizes contemporary societies.

As Guitierrez-Mora and Oto-Perialías (2022) note, it is not particular surprising that minorities are under-represented in commemorative street names since the latter express the predominant socio-political order. Women surely do not constitute a minority but they are historically categorized as a marginalized group and are underrepresented in the public sphere. For instance, McDowell (2008) studies commemorative street names after the Troubles in Northern Ireland and what emerges is that, although women play a crucial role in the conflict, men are the architect of commemoration choices and privilege male's narratives, writing out women participants. The same attitude is recorded in South Africa where Forrest (2018) examines street renaming process in Durban and certifies the failure of post-colonial and post-apartheid project of rebalancing women presence in power dynamics. As Guitierrez-Mora and Oto-Peralías (2022) highlight, the main factors that generate gender bias in street naming is the lack of women in decision-making roles and the persistence of a patriarchal culture. The authors' work purses two purposes. Firstly, they use text-analysis to measure gender gap in Spanish cities and build a composite indicator in order to describe the percentage of streets with female names over the total streets with male and female names. Then, authors analyse the correlation between the composite indicator and variables concerning gender values and attitudes. Their results suggest that using streets names constitutes a useful tool to measure gender bias at city level. Furthermore, they find that, even if increasing, the percentage of female street name is still far from parity in the period under consideration. In addition, Bigon and Zuvalinyenga (2020) highlight how this male predominance in place naming enforces the idea that male names in streets is “normal” in the public sphere. The authors observe this attitude focusing on Sub-Saharian Africa’s cities and evidence how the exclusion from the urban space affects both political experiences and well-being of women.

In the literature, most of the studies concerning street names and gender gap focus on specific case studies. For instance, Yu (2014) considers gendered space within city of Anping in Taiwan and, interviewing participating agents, finds that the prevalence of male names in streets contributes to reinforce gender stereotypes and the patriarchal perception of women within society.

Finally, it is useful for this work’s purposes to provide a brief overview of gender gap. Gender gap is defined as “gap in any area between women and men in terms of their levels of participation, access, rights, remuneration or benefits” (European Commission, 1998). Literature about gender gap is wide and the gender difference assumes several forms as it is reflected in social, political, economic and cultural attitudes. Methods for measuring the gender gap have long been debated in the literature and, in this vein, many indicators that attempt to capture the multidimensionality of the phenomenon have been developed. For instance, the World Economic Forum annually publishes the Global Gender Gap Index which benchmarks the current state of gender gap and tracks progresses, taking into consideration four key dimensions: economic participation and opportunity, educational attainment, health and survival and political empowerment.

It is also interesting, according to the aim of this work, to review different research strands focused on the perception towards gender equality.

Most times, gender inequality are fostered by gender stereotypes. The UNDP (2020) reports that about 91% of men and 86% of women present some form of gender bias in several areas like politics, education, economics and physical integrity. Gender attitudes are very relevant both for the decision-making processes and for the division of housework within families, as well as for countries’ policies. For instance, Coltrane (2000), reviewing works about household labour, finds that, although increasing overtime, women still do at least twice as much as men do in terms of housework in the 1990s in America. Furthermore, also Bianchi et al. (2000) record an increase in American men’s housework time in four different years (1965, 1975, 1985, 1995), reaching a third of total housework time in the 1990s. On the other hand, the number of overall hours that women dedicate to housework is declined mainly due to increased participation in labour force, later marriage and fewer children since the 1960s.

Among others, many studies aim to analyse factors that characterize attitudes towards gender equality. Some works claim that gender attitude is fostered by cultural and family background. For instance, Kargesten et al. (2016) aim to explore factors that globally shape gender attitudes in adolescent individuals across diverse cultural settings through a systematic literature review. The authors find that globally young people's attitudes is stereotyped and depends on individual sociodemographic features like sex, race, age, etc. Furthermore, they highlight that family and peer opinions influence adolescents' gender attitudes and these processes differ between boys and girls. Gubernskaja (2010) points out another notable aspect of gender equality, that is, changes in attitudes towards marriage and children in Austria, Germany, Ireland, the Netherlands, the U.S. and Great Britain. She analyses data from International Social Survey Programme (ISSP) in 1988, 1994 and 2002 finding that, in all the involved countries, the most educated, not married and employed women highlight less traditional view about marriage and children. Furthermore, especially in Germany and Austria, traditionalism of married people may be fostered by conservative gender attitude policies supporting the breadwinner family type and discouraging women's balance between work and children care.

Another key point in changing attitudes towards gender equality is women's participation in labour force. For instance, Seguino (2007), using World Value Survey (WVS) data, investigates the factors which determine norms and stereotypes both overtime and across countries. She finds that women's paid employment fosters more equitable gender direction. However, it is difficult to interpret results on the effects of economic growth: as the economic pie grows, less male resistance to female empowerment takes place even if economic status is shifting in favour of women. On the other way round, the study points out that in period of economic crisis patriarchal attitudes re-emerge.

Moreover, as reported in Kyoore and Sulemana (2019), most empirical studies show that education is an important predictor of gender equality. For instance, the authors, exploiting "Wave 6" of the World Value Survey, study the linkage between educational attainments and attitudes towards gender equality in five African countries (Ghana, Nigeria, Rwanda, South Africa and Zimbabwe).

Findings show that a higher level of education is correlated to more liberal attitudes towards gender equality.

Surely, also politics is another crucial field where gender bias emerges. Kantola and Augustin (2019) interview 18 Finnish and Danish women member of the European Parliament in order to explore their perceptions of gender equality within political groups. Results suggest that party groups share gendered norms and concrete practices to close the gap. However, authors observe the lack of political willingness to handle the problem of m/paternity leaves rights within the European Parliament parties. This obviously leads to enforce exclusionary practices within the institution.

Furthermore, to close the gender gap, many countries have implemented specific programmes and policies which targeted both women and men. For instance, Field et al. (2010) explore how traditional institutions in India influence women's business activity. The authors randomly assign a training programme in basic financial and business skills to poor female entrepreneurs and encourage them to reach concrete financial aims. Indian women have a similar educational background, but belong to different religions and castes which bring women to react differently to traditional restrictions. In fact, paper's results show that among Hindu women the training programme leads to an increase in borrowing and business income for upper caste women, who face greater restrictions than lower caste women; while Muslim women, who also face great social restrictions, fail to take advantage from the training. Therefore, the authors suggest the presence of a non-monotonic link between the capacity to benefit from training programme and social constrains.

Another key point in closing gender gap consists in programmes which improve access to infrastructure and information for women. For instance, Jensen and Oser (2009) analyse, exploiting an individual-level panel dataset (Survey of Aging in Rural India - SARI), the effects of introducing cable television on status of women who lives in rural India. The results suggest that this novelty corresponds to a decrease in the reported domestic violence toward women and in son preference, as well as an increase in women's empowerment and a reduction in fertility.

As previously mentioned, some programmes aimed at changing attitudes towards gender equality are specifically addressed to men which are traditionally subjected to "masculinity stereotypes". In fact, men often act as the traditional norms inherent in patriarchal culture impose as duties. For this reason, as well-exposed in current literature (see Courtenay 2000), it is crucial to actively involve men in gender equality agenda and programmes globally. Connel and Messerschimdt (2005), retracing academic works since the early 1980s, highlight how hegemonic masculinity has evolved overtime and suggest some reformulation of the concept in four different areas. However, as reported in Ricardo et al. (2011) findings about education programmes' effectiveness from literature are mixed and not always effective. Recently, Dhar and Jayachandran (2022) conduct an experiment at school level in India aiming at testing how much it is possible to change societal norms which restrict female's opportunities. The authors propose a classroom discussion between female and male adolescents in 314 schools about gender equality for two years and finds that the programme shape attitudes, making people more supportive of gender equality. A result which is not temporary: two years after the programme has ended, the researchers resurvey participants and show that the positive effect persists. Furthermore, Bulte et al. (2016) explore, through a randomized control trial, the effect of a business training for female clients of a microfinance institution in Vietnam. Authors, combining two different surveys, consider the impact on four different elements: business knowledge, practices, outcomes and firm's entry and exit decisions both in the short and medium term. In addition, the researchers also introduce the presence of women's husbands during trainings for a subsample. They find positive impact on all outcomes of interest. In fact, training improves knowledge, rises uptake of new business practices and brings an increment in profits. Furthermore, they evidence a weak additional impact of including men in the training: treatment effects on profits and sales increase when husbands are involved in the training, nevertheless they are statically negligible.

Another interesting study regarding gender equality perception is presented by Nguyen and Tarp (2022). Authors randomly select two groups of Vietnamese married men in four different rural provinces and ask to the first group to make comments on gender-related laws and to the second one to produce stories about gender equality. Results show that in the former group gender bias is not reduced, while in the latter prejudices against women dramatically diminish. However, authors highlight how changing perceptions is easier than changing behaviour. In fact, being exposed to gender equality information does not necessary correspond to an increase in husbands' involvement in housework and childcare. Therefore, findings suggest the need of policy makers' stronger interventions which it is likely to occur in the long run.

Generally, literature about gender equality perception is wide and various. However, this strand of research mainly lacks works that adopt methods to evaluate quantitatively the attitudes towards gender equality. Some exceptions are present and represented by Gubernskaya (2019) and Nguyen and Tarp (2022) which evaluate programmes' effects adopting an Ordinary Least Square (OLS) methodology. In addition, an interesting econometric attempt is provided by Bulte et al. (2016) which try to establish a causal effect of the policy adopted through a difference-in-differences approach.

This work tries to fill this gap and to enlarge the literature by analysing the relation between the individual perception of young Italians towards gender equality and the share of streets named after female in their municipality of residence with a quantitative approach based on a probit estimation.

To the best of our knowledge, we are the first that investigate the issue of gender equality perceptions through the lenses of place naming with respect to Italy, thus validating the external validity of results found in other contexts. Furthermore, findings refer to a more challenging sample since it is composed of young adults aged 20-35. Therefore, whether the relation holds in our sample, results strengthen the power of toponymy in highlighting the persistence of culture and values.

3 Data and Identification Strategy

3.1 Gender Perceptions in Italy

As Mask (2020) writes, “street names are places of memory, they hand down the past in public space”. Zucchi (2023) emphasises the difference between toponymy and odonymy. The former refers to place: it includes, therefore, city names, regions and geographical specifications, and is more difficult to change over time (e.g. Via Trieste, Via Trento). The latter can be seen as a subcategory of toponymy and refers to the naming of streets, thus being more subject to change as it follows social changes and historical events.

The use of odonymy for commemorative aims has an important social function as it identifies citizens' residences for tax and registry purposes. In Italy, the use of street names for commemorative purposes is recent. In fact, with the Unification of Italy, it became necessary to create common values in which the newly-born Italian people could recognise themselves. As Gentile (2014) suggests, toponymy takes on a function of civil pedagogy and is part of the so-called “*civil religion”* of Enlightenment matrix. The author claims that “this term is used to define a system, more or less elaborate, of beliefs, myths, rites and symbols, which confers a sacred character to an entity of this world, making it the object of worship, devotion and dedication”.
Initially, odonymy was unrelated to political events, but it made use of territorial peculiarities, places of worship or dialectal expressions, e.g. '*calle*' in Venice, (Ihl, 2002).
With the advent of post-unification politics, the objective of the so-called historical left (i.e. the political movement that took over power in the last quarter of the 19^{th} century) is to “*make the Italians”* (Banti, 2011). Thus, a process of naming streets after the *patres patriae* (Cavour, Mazzini, Garibaldi, Vittorio Emanuele) who helped create the Italian state began.
After the end of the liberal era, fascism realised the potential of odonymy’s appropriation for propaganda purposes to increase public consensus. During fascism, references to ancient Rome, the First World War and colonial companions in the streets of Italian cities became increasingly frequent. The law that still regulates odonymy in Italy dates back to the fascist era and is the number 118 of 13 June 1927. The latter gives indications for the introduction or change of street names. After the fall of the fascist regime, odonastics was subject to a process of restoration of the

previous names and, since the 1960s, new names have been dedicated to the new concepts of Constitution, Republic and Peace (Ridolfi, 2017; Ravveduto, 2018).

Currently, the naming of public places and traffic areas is the responsibility of the municipal council. With Circular No. 18 of 29 September 1992, the prefects may authorise the naming of public places after persons who have been deceased for less than ten years, subject to the presentation by the municipal administration of documentation justifying the choice and the attachment of the curriculum vitae of the recipient of the dedication. This procedure incontrovertibly shows the degree of closeness the community wishes to demonstrate to most important citizens. If, on the other hand, a change of name is desired, the superintendency expresses its opinion on the appropriateness of the change (Vitolo, 2021).

In the several processes of naming and renaming public places, a marginal space is reserved to female figures. While this trend is attributable to cultural causes, independent of women's will, who have always had little space in the public sphere, it is also true that prominent female figures are underrepresented in cities. In this regard, the Italian case is emblematic and data about streets named after female are sticking: among the 21 Italian provincial capitals, only 6.6% of streets is named after women and, excluding saints and blessed, the figure decreases to 3.9%[5]. Awareness of this gender gap has given rise to various initiatives including the Toponomastica Femminile association[6], which has mapped the streets of all Italian municipalities, highlighting the wide gap between streets named after men and those named after women. Lately, semi-automatic methodologies have also been developed (Zucchi, 2021) which, using QGIS technology, provide a mapping of the odonomastic situation at national level. For example, if one analyses the top 100 most frequent names in 107 medium-sized cities (population between 20 and 50 thousand inhabitants), the first women's names are recorded in 94th and 100th place and are Santa Lucia and Grazia Deledda (Nobel prize winner for literature in 1926), respectively. As evidence of a growing attention to women's toponymy, some relevant initiatives have been taking place in Italy. One example is the administration of Naples[7], which has made compulsory to name one street after a man and one after a woman. In the municipality of Barberino Tavernelle[8], for example, the

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[5] Data source: https://italy.mappingdiversity.eu/

[6] https://www.toponomasticafemminile.com

[7] Comune di Napoli, *Regolamento comunale per la toponomastica e la numerazione civica*, 22 febbraio 2021.

[8] Ufficio stampa associato del Chianti fiorentino, *Venti donne per venti strade 'doppie' da rinominare a Barberino Tavernelle*, in "Go news" 13 marzo 2021.

municipal administration has proposed eliminating the double naming of streets and replacing them with those of female figures proposed by the citizens themselves.
For the sake of simplicity, throughout the paper the generic term toponymy will be adopted also when referring to odonymy.

3.2 Data

This study mainly relies on the combination of two databases: "*Osservatorio Giovani*" survey by IPSOS and "*Censimento della popolazione e delle abitazioni*" by ISTAT.
The first data source is provided by IPSOS for the "Giuseppe Toniolo Institute of Higher Education" and it consists of national individual-level survey on a wide range of themes.[9] The survey's purpose is to provide a comprehensive picture of the Italian young people and to describe their understanding of society's evolution. For the purposes of this work, the year 2017 is taken into consideration. In this year, 3,034 individuals between 20 and 35 years participate in the survey. The great advantage of this dataset is its uniqueness of information at individual-level: along with the respondents' answers on a wide range of topics, it includes information about standard individual characteristics such as age, education, marital status and gender.
Alongside data provided by IPSOS, this analysis exploits data about geographical, historical, and socio-economic characteristics at municipal level mainly collected by ISTAT in "*Censimento della popolazione e delle abitazioni"* and in the "*Atlante Statistico dei Comuni*".
The next sub-paragraphs examine more in depth all the sources and variables adopted in this study.

Gender Equality Perception

Starting from the questionnaire "Osservatorio Giovani", a dummy variable is built aiming at describing the individuals' gender perception. The dependent variable of the analysis is a dummy variable based on the respondents' personal judgement on the following statement: "In general, men are better political leaders than women". This variable is called *WomenLeader*. The other outcome taken into consideration in the analysis for robustness check is called *WomenManager*;

[9] "*Rapporto Giovani*" database contains results of the survey conducted on a sample of young people aged 18 to 34 years. Promoted by the Istituto di Studi Superiori Giuseppe Toniolo (in collaboration with the Università Cattolica del Sacro Cuore and with the support of Fondazione Cariplo and Intesa San Paolo) and carried out by Ipsos, the "Rapporto Giovani" is an in-depth and extensive research on the world of youth in the last decade.

in this case, the respondents are asked to give an opinion about the statement "In general, men are better managers than women".

For each statement, the respondents have to choose an answer in a range that goes from "*Completely disagree"* to "*Totally agree"*. If the answer to the claim is "*Completely disagree*", values are coded as 1, otherwise 0. Among the questions related to attitudes towards gender equality, the choice of the main outcome of interest is driven by the fact that still nowadays politics in Italy is a male prerogative, despite the recent appearance of female figures at the top of the country's two main political parties.[10] As far as the alternative outcome (*WomenManager*) is concerned, the data are even worse: the percentage of women chief executive officers (CEO) in Italy is 3% in 2021, a decreasing figure with respect to 2020 when it was at 4%.[11]

Female street names

The "*Censimento della popolazione e delle abitazioni*" provided by ISTAT records all streets in Italy and attributes a unique code for roads in each municipality. Therefore, the starting point is the exploration of this huge dataset which counts about 21 million observations. First, we counted the number of streets in each municipality. Then, we extracted and we counted the street named after women in each municipality by considering around the first thousand female names listed as the most common female street names.[12] What is particularly striking is that only the 6.6% of streets is named after females and, excluding saints and blessed, this percentage decreases even until 3.9%. Among the 21 Italian capital provinces, Bolzano is the first in the ranking for streets named after women with a percentage of 13%, while Aosta is at the tail end with just two streets that celebrate female figures over the 73 streets dedicated to people.

It is important to note that the extraction of streets named after female figures required a number of fundamental steps. Initially, the textual analysis is conducted by precisely searching for the names (and, if present, also the family names) in the initial list. Subsequently, it is allowed to search the text for even a single part of the initial name (e.g. only the first name). This second step made it possible to count a larger number of streets not captured in the first round of analysis, but

[10] *Inter-Parliament Union* (IPU) reports that in 2023 in Italy 35.7% of parliament are women. For further details, see: https://www.ipu.org/parliament/IT

[11] Data are taken from the European Women on Boards Gender Diversity Index (2021). For further details, see: https://europeanwomenonboards.eu/wp-content/uploads/2022/01/2021-Gender-Diversity-Index.pdf

[12] Precisely, 918 female names are selected considering the Italian 21 capital provinces. These names are taken from https://italy.mappingdiversity.eu/ . The list of the first 50 most used names and the relative descriptive statistics are provided in Appendix, while full list of name used in this analysis is available upon request.

also included possible distortions. For this reason, after an initial automated selection, the extracted names are analysed manually. For example, some streets may contain names difficult to treat because either a same name can be used both for male and female (e.g. “Andrea”) or due to the combination of one female and one male name (e.g. “Filippo Maria”).

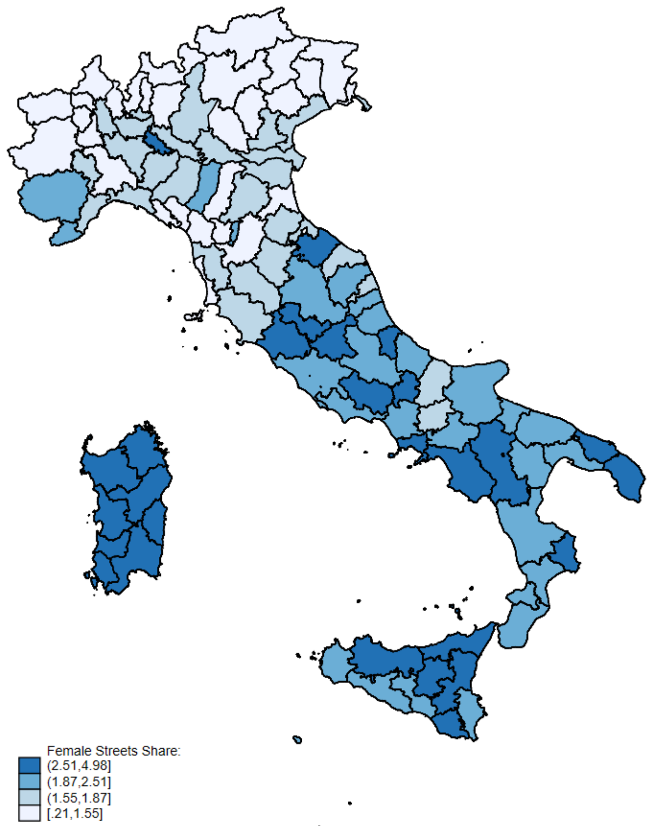
Finally, a street-name indicator of female share is identified:

$$FS_m = \frac{F_m}{M_m + F_m} x100 \quad (1)$$

Where M_m and F_m capture the number of streets in the municipality m including names which refer to men and women, respectively. The variable is called *Female Streets*.

Figure 1 reports the intensity of share of female streets at NUTS-3 level in Italy. Here, colour blends from light to dark blue according to the number of streets named female for each NUTS3 region. It is pointed out that in the islands (e.g. Sardegna and Sicilia) and in South Italy is concentrated the majority of street entitled to women.

Figure 1: Female streets share at NUTS-3 level



Note: female streets share across the Italian regions.
Source: authors'elaboration from "*Censimento della popolazione e delle abitazioni*" by ISTAT.

Controls

In this study, several sets of control variables are taken into consideration. Firstly, some variables are individual level controls: we collected data on individual variables related to age, educational attainment, marital status, religious beliefs and gender. In particular, we construct a dummy variable which takes value 0 whether the respondent is religious (go to church every week, every month or at least sometimes in a year) and 1 otherwise (never goes to church, or anyway just in really unusual occasion). Controlling for religion could be relevant due to the strong presence of Catholic Church which historically fosters a patriarchal culture (Attoh, 2017; Casanova, 2009).

Secondly, a group of variables include geographic controls. First, since it is plausible that in more remote areas the attitude to gender equality is feebler, we include a dummy variable which is coded as 1 if the municipality is considered an urban centre, while otherwise is coded as 0.[13] In the same spirit, we include in the set of geographic controls an index of terrain asperity of each municipality.[14] As a proxy for accessibility, since historically, seaside towns are recognised as a melting pot of cultures and are characterized by more open-minded inhabitants (Abulafia, 2011; Braudel, 1995), we also account for the distance from the sea. In particular, we calculated the geodetic distance between each municipality's centroid and the nearest point on the Italian coastline.

Furthermore, variables related to socioeconomic context of individuals' municipality of residence are entailed in the analysis. To account for different economic development levels, we take into account the growth rate of population between 2001 and 2017 and the average municipal income. Data are provided by ISTAT in the "Atlante Statistico dei Comuni". Furthermore, we control for the resident population in 2017 because we believe that, with the same number of streets named after women, larger cities are more likely to have the respondent aware of the existence of certain streets. In the same spirit, we control for historical size of city, exploiting data from Guiso et al. (2016). Specifically, a dummy variable is created according to the size of cities in the 1300s: it assumes value 1 if the population in 1300 exceeded 10,000 people, and 0 otherwise.[15] As far as the productive structure is concerned, the number of local units of manufacturing firms operating in Italy in 2017 is taken into consideration. Moreover, from Schaub and Morisi (2020), data about the number of people without high-speed internet connection are collected.[16] It is noteworthy that internet use is a powerful tool in transmitting values overtime and across generations. In addition, this analysis takes into account also police expenditure over the total expenditure in order to capture the relevance that each municipality devote to social security. [17] Regarding social capital, the analysis exploits data about the number of non-profit associations at the municipal level (2001), weighted by resident population (Collischon and Eberl, 2021).[18]

[13] This variable is created starting from data provided by Shaub and Morisi (2020)

[14] The index of terrain asperity is calculated starting from Nunn and Puga (2012).

[15] Information on city size are taken from Bairoch et al. (1988), who report the population of European cities between 800 and 1850, approximately every 100 years. Although there are population data referring to earlier periods, 1300 is the first year in which there are only few missing data.

[16] Data available in Schaub and Morisi (2020)'s Online Appendix. The data are provided for the years ranging from 2012 to 2015, while in this study we refer to the year 2015.

[17] Data available in Bove et al. (2019).

[18] Data related to measures of social capital for Italian provinces and municipalities are available at Tommaso Nannicini's personal website: https://www.tommasonannicini.eu/it/works/measures-social-capital-italian-provinces-and-muni/ .

Finally, also a set of controls regarding political issue is introduced. Firstly, seven variables describing the percentage of votes for Christian Democracy in the national elections at municipal level respectively in 1958, 1963, 1968, 1972, 1979, 1987, 1992.[19] Since the municipal council decides street names, it is reasonable to control for national political direction in a period of great social transformations. In this study, data from national elections are purposely taken into account instead of municipal elections because, due to the massive presence of civic lists at local level, the data may be too fragmented. This is the reason why only the parties of the parliamentary arc are taken into consideration.

In addition, another interesting control is constructed starting from the birthplace of those women who wrote the Constitution, i.e. "Founding mothers”. It is likely that people who live in (or quite near) a municipality that is the birthplace of such a prominent figure in Italian politics are, at least partially, influenced in their gender equality perception. We collected information on the birthplace of each “founding mother” and we computed a matrix of distances between the latter and each municipality’s centroid. Starting from the matrix of distances, we constructed a dummy variable that assumes value 1 if the municipality is within 20 km to the founding mothers’ birthplace.

To conclude, we report in Table 1 descriptive statistics of all the variables described above. Since in this study we use data at both individual and municipality level, variables are divided in *Individual variables* and *Municipal Level Variables*.

[19] Source: Ministry of Home Affairs, available at: https://elezioni.interno.gov.it/

Table 1: Descriptive Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Individual Level Variables					
Age	2,888	29.216	4.167	20	35
Educational Attainment	2,888	2.587	.728	1	4
Marital Status	2,888	1.277	.485	1	5
Gender (Male=1 Female=0)	2,888	1.635	.482	1	2
Religiosity	2,888	.576	.494	0	1
WomenLeader	2,888	.856	.351	0	1
WomenManager	2,888	.854	.353	0	1
Municipal Level Variables					
Population Growth (lnPop2017-lnPop2001)	1,213	.07	.125	-.509	.703
Income Per Capita	1,213	1321296.2	379349.76	457040.63	3595310.5
Manufacturing Firms	1,213	182.982	498.172	1	9339
Broadband Coverage	1,213	.01	.018	0	.267
Police spending (per capita)	1,213	35.93	21.77	0	254.434
Ruggedness	1,213	1.317	1.579	0	8.667
Urban Area (Urban=1 Rural=0)	1,213	209.723	.448	209	210
Distance from the Sea (within 20km=1 otherwise=0)	1,213	.383	.486	0	1
Medieval Large city (Yes=1 No=0)	1,213	.035	.185	0	1
Non Profit Association (per capita)	1,213	.004	.002	0	.018
% DC votes in 1958 National Election	1,213	46.916	14.098	13.013	94.888
% DC votes in 1963 National Election	1,213	43.612	14.275	11.781	93.462
% DC votes in 1968 National Election	1,213	44.019	13.99	5.099	89.747
% DC votes in 1972 National Election	1,213	43.431	13.684	9.417	90.683
% DC votes in 1979 National	1,213	42.228	12.544	5.593	87.846

Election					
% DC votes in 1987 National Election	1,213	37.535	11.698	3.734	83.135
% DC votes in 1992National Election	1,213	32.415	11.414	3.824	77.664
Near birthplace of a "constituent mother" (within 20km=1 otherwise=0)	1,213	.093	.291	0	1
Share of Female Street Name over total (*Female Streets*)	1,213	2.179	1.801	0	21.25

Sample: young adults aged 20-35 in 2017.

3.3 Identification Strategy

The main analysis of this study relies on multivariate standard probit regressions that are used to assess how and to what extent the percentage of female street names in a municipality is related to individuals' gender equality perception. [20] We are interested in how the probability of having a more egalitarian perception of women's role in society changes according to different percentage of streets named after female over the total.

The Probit model to which we refer can be expressed as follows:

$$\Pr\left(WomenLeader_{i,m,r} = 1 \mid FemaleSteets_m, X_{i,m}, Z_m, \mu_r\right) = \Phi\left(\alpha + \beta FemaleSteets_m + \gamma X_{i,m} + \delta Z_m + \mu_r\right) \quad (2)$$

where the dependent variable, $WomenLeader_{i,m,r}$, is the binary perception towards gender equality attitudes for individual i in municipality m and region r, specifically towards female figures as political leaders, and Φ is the standard normal distribution function. The dependent

[20] The standard probit is based on the assumption that random errors are normally distributed with zero mean and unit variance. This means that the analysis is based on the standard cumulative normal distribution function, which was used to model the relationship between the binary response variable and the explanatory variables.
In the case of the probit model, the identification strategy is based on maximising the model's likelihood function, which describes the probability of observing the data given the model parameters.

variable assumes value 1 if individuals do not believe that men are better political leader than women, while it assumes value 0 otherwise. The key explanatory variable is $FemaleStreets_m$ and represents the percentage of streets named after women in municipality m. The sign of the β coefficient associated to this variable indicates if an increase in $FemaleStreets_m$ leads to an increase or a decrease in the probability of $WomenLeader_{i,m,r} = 1$. $X_{i,m}$ is the vector of personal controls at individual level (age, gender, educational attainment, marital status, religiosity), while Z_m is the vector of controls at municipal level and it entails geographical, socio-economic, social capital, historical and political controls.[21] Finally, μ_r represents regional fixed effects: while we generally refer to NUTS-3 regional fixed effects, in some specifications we also refer to 20 binary variables, one for each Italian NUTS-2 region.

[21] An in-depth explanation of all variables is provided in Section 3.2.

4 Results

4.1 Main Results

In this section, we present the main results obtained by estimating the probit model presented in Equation 2. Table 2 presents different specifications of the model, according to the different set of controls included and the regional fixed effects used. It is worth noting that the Table 2 shows the marginal effects of a unit increase in the variable $FemaleStreets_m$ on our dependent variable, $WomenLeader_{i,m,r}$. In particular, in the first column estimates of the baseline specification are reported, where only NUTS-3 regional fixed effects are taken into account. In the successive columns, different sets of controls are progressively added and the marginal effects remain significant in all specifications. In Column (2), personal, and geographical controls enter the model. In Column (3) and Column (4) socio-economic and social capital controls are added, respectively. In Column (5) we control for historical variables, while in Column (6) political controls are included. In all specifications the positive sign of the marginal effect shows that an higher presence of female names in streets increase the probability of having a positive attitude towards gender equality. Finally, in Column (7), the most complete specification is re-estimated including NUTS-2 regional fixed-effects instead of NUTS-3 regional fixed-effects.[22] Also in this specification, the marginal effect of an increase in the percentage of streets named after women is positive and significant. Overall, results suggest that one unit change in the percentage of streets named after women, increases the probability of having a more equitable gender perception by 1.3-1.6%. Finally, it is worth noting that in all specifications reported in Table 2 standard errors are clustered at the NUT3-level. What is outstanding to stress is the stability of the results across all the specifications.

[22] It is worth noting that the difference in the number of observations is due to computational reasons related to the estimation of Probit model, i.e. the number of observation deleted in the process changes according to collinearities detected by the algorithm.

Table 2: Main Results

	Dependent Variable: *WomenLeader* $_{i,m,r}$,						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$FemaleStreets_m$	0.0143^{**}	0.0133^{*}	0.0157^{**}	0.0160^{**}	0.0158^{*}	0.0162^{*}	0.0159^{**}
	(0.00714)	(0.00703)	(0.00801)	(0.00808)	(0.00811)	(0.00854)	(0.00732)
NUTS-3 FE	X	X	X	X	X	X	
Personal		X	X	X	X	X	X
Geography		X	X	X	X	X	X
Socio-Economic			X	X	X	X	X
Social Capital				X	X	X	X
History					X	X	X
Politics							X
NUTS-2 FE							X
N	2750	2750	2750	2750	2750	2750	2885

Note: Results in all specifications refer to the probit model estimated according to Equation 2. Reported coefficients refer to the marginal effect on *WomenLeader* $_{i,m,r}$, of one unit change in $FemaleStreets_m$.The dependent variable is the dummy variable related to gender perception towards female political leaders, *WomenLeader* $_{i,m,r}$, and it remains unchanged in all different specifications. The main independent variable is the variable $FS_m$the percentage of streets named after female. Personal controls include: age, educational attainment, marital status, gender, religiosity. Geographical controls (at the municipal level) include: an index of terrain asperity, the geodetic distance from the sea and a variable related to whether a city is a rural or urban area. Socio-economic controls (at the municipal level) entail: average income per capita of the municipality of residence, the number of manufacturing firms in 2017, resident population in 2017, population growth from 2011 to 2017, police expenditure and broadband coverage. Social-capital is measured by the number of non-profit associations per capita in each municipality in 2011. Historical control consists of a dummy variable that accounts for the size of city in year 1300 C.E. Political controls encompass: seven variables describing the percentage of votes for Christian Democracy in the national elections at municipal level respectively in 1958, 1963, 1968, 1972, 1979, 1987, 1992 and a dummy variable, *FoundingMothers*, related to the distance from founding mothers' birthplace. All specifications in Columns from (1) to (6) include NUTS-3 regional Fixed Effects at NUTS-3 level, while in column (7) NUTS-2 region Fixed Effects are used. Standard errors in parentheses are clustered at NUTS-3 level. The statistical significance of the test that the underlying coefficients is equal to zero is denoted by: * $p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$.

4.2 Robustness analysis

This section validates the empirical approach by running some robustness checks. One of the first concerns regards the choice of the dependent variable; therefore, the model is estimated considering another outcome. Specifically, another measure that alternatively captures the relationship between gender perception and the number of streets named after women is what is called in the analysis *WomenManager*. Starting from the questionnaire "Osservatorio Giovani", this variable is a dummy aiming at describing the individuals' gender perception. In this case, the respondents are asked to give an opinion about the statement "In general, men are better managers than women". The respondents are asked to choose an answer in a range that goes from "*Completely disagree"* to "*Totally agree"*. If the answer to the claim is "*Completely disagree*", values are coded as 1, otherwise 0. This question within the survey is chosen because even today in Italy the percentage of women on company boards is low in several types of companies (e.g. 22% in corporations, 7% in listed companies and 6% in banking companies in 2011[23]). Table 3 reports the main results for the probit model with the alternative outcome. Findings confirm the robustness of the results which remain substantially unchanged with respect to the main outcome's results[24].

Table 3: WomenManager Probit estimation

	Dependent Variable: ***WomenManager***						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$FemaleStreets_m$	0.0102	0.00916	0.0108	0.0108	0.0110*	0.0126**	0.0140**
	(0.00719)	(0.00626)	(0.00682)	(0.00681)	(0.00653)	(0.00629)	(0.00550)
NUTS-3 FE	X	X	X	X	X	X	
Personal		X	X	X	X	X	X
Geography		X	X	X	X	X	X
Socio-Economic			X	X	X	X	X
Social Capital				X	X	X	X
History					X	X	X
Politics						X	X
NUTS-2 FE							X
N	2793	2793	2793	2793	2793	2793	2885

Note: all specifications are estimated by probit. The dependent variable is the dummy variable related to gender perception towards female manager, $WomenManager_{i,m,r}$, and it remains unchanged in all different specifications shown in the Table. The main independent variable is the variable $FemaleStreets_m$ the percentage of streets named after female. Personal controls include: age, educational attainment, marital status, gender, religiosity. Geographical controls (at the municipal level) include: an index of terrain asperity, the geodetic distance from the sea and a variable related to whether a city is a rural or urban area. Socio-economic controls (at the municipal level) entail: average income per capita of the municipality of residence, the number of manufacturing firms in 2017, resident population in 2017, population growth from 2011 to 2017, police expenditure and broadband coverage. Social-capital is measured by the number of non-profit associations per capita in each municipality in 2011. Historical control consists of a dummy variable that accounts for the size of city in year 1300 C.E. Political controls encompass: seven variables describing the percentage of votes for Christian Democracy in the national elections at municipal level respectively in 1958, 1963, 1968, 1972, 1979, 1987, 1992 and a dummy variable, *FoundingMothers*, related to the distance from founding mothers' birthplace. All specifications include regional Fixed Effects at NUTS-3 level. Standard errors are clustered at NUTS-3 level. The statistical significance of the test that the underlying coefficients is equal to zero is denoted by: * $p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses.

[23] Banca D'Italia, Consob, Dipartimento per le Pari Opportunità. *La partecipazione femminile negli organi di amministrazione e controllo delle società italiane*, 2021.

[24] The model is also validated changing the estimation method, adopting a linear probability model with both outcomes. Results remain positive and significant and are available upon request.

Secondly, the other robustness check consists of re-running the main specification changing the main explanatory variable, i.e. the share of streets named after women, transforming the continuous variable in a discrete one. Therefore, a dummy variable is created: it assumes value 1 if the percentage of streets named after women is greater than the median, while is 0 otherwise. The variable is called $Dummy\_share_m$. Table 4 shows that the marginal effects remain positive and significant. In this case, the magnitude of the effect is greater in comparison to the main specification's results. Indeed, the effect of having one additional percentage point of streets named after women in the most complete specification increases the probability of having a more equitable perception towards gender equality by 4%. This corresponds to around the double with respect to the main specification with the continuous variable.

Table 4: Dummy Share of female streets, probit estimation

	Dependent Variable: *WomenLeader*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Dummy\_share_m$	0.0377*	0.0354*	0.0488**	0.0491**	0.0485**	0.0480**	0.0368*
	(0.0201)	(0.0197)	(0.0211)	(0.0211)	(0.0211)	(0.0228)	(0.0205)
NUTS-3 FE	X	X	X	X	X	X	
Personal		X	X	X	X	X	X
Geography		X	X	X	X	X	X
Socio-Economic			X	X	X	X	X
Social Capital				X	X	X	X
History					X	X	X
Politics						X	X
NUTS-2 FE							X
N	2750	2750	2750	2750	2750	2750	2885

Note: all specifications are estimated by probit. The dependent variable is the dummy variable related to gender perception towards female political leaders, $WomenLeader_{i,m,r}$, and it remains unchanged in all different specifications shown in the Table. The main independent variable is the dummy variable $Dummy\_share_{i,m,r,}$: it assumes value 1 if the percentage of streets named after women is greater than the median, while is 0 otherwise. Personal controls include: age, educational attainment, marital status, gender, religiosity. Geographical controls (at the municipal level) include: an index of terrain asperity, the geodetic distance from the sea and a variable related to whether a city is a rural or urban area. Socio-economic controls (at the municipal level) entail: average income per capita of the municipality of residence, the number of manufacturing firms in 2017, resident population in 2017, population growth from 2011 to 2017, police expenditure and broadband coverage. Social-capital is measured by the number of non-profit associations per capita in each municipality in 2011. Historical control consists of a dummy variable that accounts for the size of city in year 1300 C.E. Political controls encompass: seven variables describing the percentage of votes for Christian Democracy in the national elections at municipal level respectively in 1958, 1963, 1968, 1972, 1979, 1987, 1992 and a dummy variable, *FoundingMothers*, related to the distance from founding mothers' birthplace. All specifications include regional Fixed Effects at NUTS-3 level. Standard errors are clustered at NUTS-3 level. The statistical significance of the test that the underlying coefficients is equal to zero is denoted by: * $p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses.

4.3 Heterogeneous treatment effects

The analysis is extended by investigating whether having a greater number of streets entitled to women increases the probability of having a higher awareness of gender equality according to individuals' characteristics or socio-economic and environmental aspects.

Firstly, the sample is split according to the level of education: individuals are divided between those who have at least a university degree and those who do not. Indeed, it is widely showed in literature that greater open-mindedness is associated to a higher level of education, thus reducing gender prejudices against women (Flabbi, 2012; Anelli e Peri, 2015). Furthermore, this is true also for individuals' parents level of educational attainment (Farrè and Vella, 2012; Nollenberger et al. (2016); González de San Román and de la Rica Goiricelaya, 2012). Therefore, the sample is also divided into another sub-sample where individuals are split between who has at least a parent with a bachelor's degree (or higher attainment) and who does not. Indeed, parent's education indirectly relates to children's academic achievements (Davis-Kean, 2005). Table 5 presents the results: the main model (Equation 2) is re-estimated in the two couple of sub-samples. Results highlight that the correlation between more equitable gender perceptions and the number of streets named after women holds when considering not graduated individuals and individuals with not graduated parents, while it disappears for those who have at least a degree. This means that the effect of having a higher percentage of streets named after female is a powerful tool to influence not-educated individuals.

Table 5: Heterogeneous effect: Educational Attainment

	Dependent Variable: *WomenLeader*			
	Individual Educational level		Parents Educational level	
	(1)	(2)	(3)	(4)
	Not Grad	Graduated	ParentsNotGrad	ParentsGraduated
$FemaleStreets_m$	0.0213**	0.00704	0.0182**	-0.00693
	(0.0103)	(0.0102)	(0.00913)	(0.0250)
NUTS-3 FE	X	X	X	X
Personal	X	X	X	X
Geography	X	X	X	X
Socio-Economic	X	X	X	X
Social Capital	X	X	X	X
History	X	X	X	X
Politics	X	X	X	X
NUTS-2 FE	X	X	X	X
Obs.	1291	1226	2063	500

Note: all specifications are estimated by probit. The dependent variable is the dummy variable related to gender perception towards female manager, *WomenManager*$_{i,m,r}$, and it remains unchanged in all different specifications shown in the Table. The main independent variable is the variable *%FemStreets*$_{i,m,r,}$ the percentage of streets named after female. Personal controls include: age, educational attainment, marital status, gender, religiosity. Geographical controls (at the municipal level) include: an index of terrain asperity, the geodetic distance from the sea and a variable related to whether a city is a rural or urban area. Socio-economic controls (at the municipal level) entail: average income per capita of the municipality of residence, the number of manufacturing firms in 2017, resident population in 2017, population growth from 2011 to 2017, police expenditure and broadband coverage. Social-capital is measured by the number of non-profit associations per capita in each municipality in 2011. Historical control consists of a dummy variable that accounts for the size of city in year 1300 C.E. Political controls encompass: seven variables describing the percentage of votes for Christian Democracy in the national elections at municipal level respectively in 1958, 1963, 1968, 1972, 1979, 1987, 1992 and a dummy variable, *FoundingMothers*, related to the distance from founding mothers' birthplace. All specifications include regional Fixed Effects at NUTS-3 level. Standard errors are clustered at NUTS-3 level. The statistical significance of the test that the underlying coefficients is equal to zero is denoted by: * $p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses.

Furthermore, the sample is split according to the municipality's dimension and the degree of urbanisation. Firstly, the sample is divided in urban centres and internal areas. What is showed in literature is that in the inland areas there is a greater sense of community than in urban ones (Belanche et al., 2021; Casakin et al., 2015; Mandal and Philipps, 2022; Cassidy and McGrath, 2015). Therefore, street names reinforce the sense of belonging and, consequently, could have a greater impact on the perception of women. Secondly, the sample is split according to population size: one might expect that in small towns with a population of less than 40,000, people would have a greater awareness of their surroundings. 40,000 is chosen because it is the median value. Therefore, one should be more influenced in terms of values perception (e.g. gender perception) in everyday life (Oto-Peralias, 2018; Yu, 2014). Indeed, Table 8 reports the results of main model's estimation in the two couple of sub-samples. Findings highlight that the correlation between gender perception and the percentage of female street names holds considering internal areas and smaller towns, whereas it disappears in urban and big centres. This trend confirms the literature describing a greater sense of community and attachment to place in less populated areas.

Table 6: Heterogeneous effect: Municipality's Degree of Urbanisation and Dimension

Dependent Variable: *WomenLeader*				
	Remoteness		Resident population	
	(1)	(2)	(3)	(4)
	Inland area	Urban area	SmallMunicip	BigMunicip
$FemaleStreets_m$	0.0387*	0.0104	0.0231**	0.0132
	(0.0212)	(0.00882)	(0.0113)	(0.0233)
NUTS-3 FE	X	X	X	X
Personal	X	X	X	X
Geography	X	X	X	X
Socio-Economic	X	X	X	X
Social Capital	X	X	X	X
History	X	X	X	X
Politics	X	X	X	X
NUTS-2 FE	X	X	X	X
Obs	305	2332	1254	1284

Note: all specifications are estimated by probit. The dependent variable is the dummy variable related to gender perception towards female manager, $WomenManager_{i,m,r}$, and it remains unchanged in all different specifications shown in the Table. The main independent variable is the variable $\%FemStreets_{i,m,r}$, the percentage of streets named after female. Personal controls include: age, educational attainment, marital status, gender, religiosity. Geographical controls (at the municipal level) include: an index of terrain asperity, the geodetic distance from the sea and a variable related to whether a city is a rural or urban area. Socio-economic controls (at the municipal level) entail: average income per capita of the municipality of residence, the number of manufacturing firms in 2017, resident population in 2017, population growth from 2011 to 2017, police expenditure and broadband coverage. Social-capital is measured by the number of non-profit associations per capita in each municipality in 2011. Historical control consists of a dummy variable that accounts for the size of city in year 1300 C.E. Political controls encompass: seven variables describing the percentage of votes for Christian Democracy in the national elections at municipal level respectively in 1958, 1963, 1968, 1972, 1979, 1987, 1992 and a dummy variable, *FoundingMothers*, related to the distance from founding mothers' birthplace. All specifications include regional Fixed Effects at NUTS-3 level. Standard errors are clustered at NUTS-3 level. The statistical significance of the test that the underlying coefficients is equal to zero is denoted by: * $p < 0.1$, ** $p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses.

5 Conclusions

As Rose-Redwood et al. 82010) claim, street names represent social, cultural and political heritage. After the French Revolution, place naming assumes a crucial role in building a shared past, beyond the primary function of spatial organization of the cityscape (Azaryahu, 1996). In particular, researchers highlight the relation between street naming and different topics such as national identity, religiosity and male hegemony.
This work focuses specifically on this latter aspect, measuring the relation between the individual perception towards gender equality of young Italians and the share of streets named after female in their municipality of residence. Following Gutierrez-Mora and Oto-Peralías (2022), this analysis exploits different data sources and constructs an index of female streets share over the total number of streets at municipal level.

Following Oto-Peralias (2018), exploiting geographical cultural data and adopting text-analysis is a good way to understand gender bias with a quantitative method. This particularly well fit in the case of Italy where street naming and renaming process is attributed by law to the municipal council. Therefore, considering toponymy as source of data can be a key element to investigate population's attitudes. Results suggest that one unit change in the measure of female streets (%) increases the probability of having a more equitable gender perception by 1.3-1.6%.

This study's contribution is multiple. First of all, it enriches the strand of literature about the use of urban toponymy to quantify social phenomenon in Italy. Secondly, to the best of our knowledge, this study contributes to the literature regarding gender perception and place naming, verifying the external validity of results found in other context (Gutierrez-Mora and Oto-Peralías, 2022). Finally, the analysis is conducted in a sample which is, in some way, even more challenging because composed of people aged 20-35.

To sum up, this work represents an innovation as it gives back a picture that captures population's attitudes towards gender equality in Italian municipalities, using a quantitative method. Definitively, a more balance representation between male and female in toponymy should be a desired outcome for a more equalitarian society.

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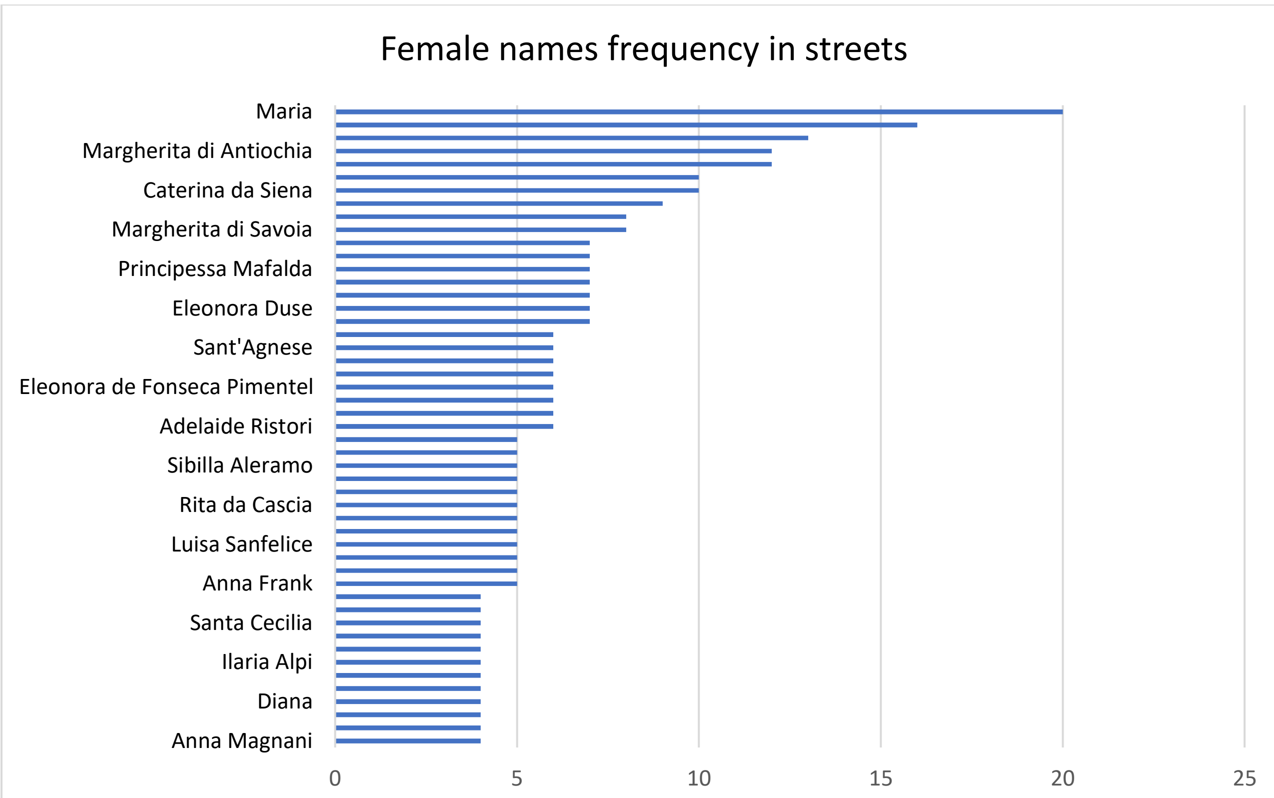
Appendix

In this Appendix, the recurrent female names in the streets in the 21 Italian provincial capitals are reported.

Figure A1: The recurrent female names in the 21 Italian capital provinces



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