Spatial variation in fertility across Europe: patterns and determinants

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Journal:	*Population, Space and Place*
Manuscript ID	PSP-19-0164.R2
Wiley - Manuscript type:	Research Article
Keywords:	Total Fertility Rate, NUTS 3, Europe, spatial regression, spatial lag model, spatial variation

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Abstract

This study investigates spatial variation in fertility in Europe. We analyze spatial variation in total fertility rates using small-scale geographical data from twenty-one European countries for 2010, and investigate the role economic, sociocultural, and spatial factors play in regional fertility levels. We compare the performance of conventional OLS regression and multilevel modeling with that of different spatial regression models and show that the spatial approach is superior for modeling regional fertility variation. The analysis shows that fertility levels in a region are strongly related to GDP per capita and the share of divorced individuals in the region, and fertility levels in neighboring regions, supporting that all three realms of fertility determinants – economic sociocultural, and spatial – are relevant for understanding modern fertility variation.

Keywords: Total Fertility Rate; NUTS 3; Europe; spatial regression; spatial lag model; spatial variation

Introduction

Fertility levels varied considerably across European countries over the last decades. Two distinct fertility regimes emerged in Europe in the first decade of this century, with one group of countries exhibiting relatively high total fertility rates, about 1.9, and the other relatively low, about 1.3 (Rindfuss et al., 2016). The first bifurcation group consists of Western and Northern European countries, whereas the second group is comprised of Central, Southern, Eastern, and German-speaking western European countries. Significant fertility variation across these countries has persisted, although recent research reports a decline in fertility levels in some 'high' fertility countries (e.g. Nordic) and an increase in some low fertility countries (e.g. Germany). This has led to a new wave of research to improve our understanding of the relationships between fertility and economic, cultural, migratory, and institutional factors (Andersson et al., 2009; Hiilamo, 2017; Jalovaara et al., 2019; Hellstrand et al., 2019).

Regional variation in fertility within countries has received significantly less attention than the variation between countries. The lack of interest is partly explained by the assumption that, while fertility levels significantly varied across space during the demographic transition (see e.g. Goldstein and Klüsener, 2014), childbearing patterns in the 'post-transitional' societies differ only negligibly across regions and settlements (Coleman, 2002). While persisting regional differences are certainly not as big as during the demographic transition, research from several countries over the last two decades has shown that fertility levels differ substantially by the level of urbanization in Europe: clearly, fertility is higher in rural areas and small towns and lower in large cities (Hank, 2001; Michielin, 2004; De Beer and Deerenberg, 2007; Kulu et al., 2007). Further, the variation in fertility levels within countries may be even larger than across countries. For example, Kulu and Washbrook (2014) reported significant variation in fertility across residential contexts in Britain in 2011: the total fertility rate for small towns and rural areas varied between 2.2 and 2.3 in 2011, the rate for city regions and towns was between 1.9 and 1.95; and the rate for the London region was about 1.8 and for the city center as low as 1.5. Further analysis demonstrated that high-fertility areas were especially important in terms of the population size; almost one third of the British population lived in areas that were classified as 'rural areas and small towns'. Clearly, there is a need to improve our understanding of why fertility varies within countries.

The aim of this study is to investigate spatial fertility variation in Europe and its related factors. We use 1,134 comparable small-scale spatial (NUTS[1] 3) units across 21 European countries to study patterns of regional variation in total fertility rates and to improve our understanding of the role economic, sociocultural, and spatial factors play in shaping regional fertility. Although recent studies have investigated spatial fertility variation in Europe, they have either focused on one country (Sobotka and Adiguzel, 2002; Kulu et al., 2007; Kulu et al., 2009; Klüsener et al., 2013b; Vitali and Billari, 2017) or used relatively large spatial units in multi-country studies (Kohler et al., 2002; Billari and Kohler, 2004; Klüsener et al., 2013a; Fox et al., 2019). These approaches hide cross-national patterns and overlook the considerable amount of local variation in fertility. The pan-European approach to subnational spatial fertility using small-scale spatial units is the first novelty of our study.

The second novelty is that we analyze the data both from a multi-level and spatial regression perspective. Conventional OLS regression or multi-level models are often used to study spatial variation in demographic processes, despite their limitations when applying them to spatial data (Bryan and Jenkins, 2015). We compare the performance of these approaches to that of spatial regression approaches, which explicitly consider the interrelationship between different spatial units (Waldorf and Franklin, 2002). We show that, in our case, the spatial regression approach is superior to the conventional approaches that do not take continuous

[1] NUTS (Nomenclature of Territorial Units for Statistics) regions are statistical units designed by Eurostat and are based on population size.

space into account, not only because spatial regression explicitly addresses the violation of critical assumptions of regression models (i.e. independence of observations), but also because it provides the opportunity to explore and determine how spatial proximity and interaction might shape observed fertility patterns.

The third novelty is that we utilize a single framework to assess the role of economic, sociocultural, and spatial factors for fertility variation at high spatial detail across many countries in Europe. Prior pan-European research has assessed either economic aspects of fertility variation (Fox et al., 2019) or social perspectives (Klüsener et al., 2013a) but not both. While other research has taken a spatial perspective on economic and social factors (Hank, 2001), these country case studies did not explicitly consider the interrelationship between different spatial units. We incorporate each aspect – economic, sociocultural, and spatial – together to provide a holistic understanding of fertility variation in Europe. This provides significant new insights into how these three aspects are related to variation in regional fertility levels across Europe.

Previous Research on Regional Fertility Variation in Europe

Urban-rural fertility variation

Previous research on spatial aspects of fertility in Europe has mostly investigated urban-rural fertility variation. Studies show that fertility levels are higher in rural areas and small towns and lower in large cities. This pattern has been observed for France (Fagnani, 1991), the Netherlands (De Beer and Deerenberg, 2007), Britain (Kulu and Washbrook, 2014), Italy (Michielin, 2004), Germany and Austria (Hank, 2001; Kulu, 2006), the Nordic countries (Kulu et al., 2007), the Czech Republic (Burcin and Kucera, 2000), and Poland (Vojtechovska, 2000; Kulu, 2006). Although there is consensus that economics, policies, and norms all influence spatial variation in fertility (Brewster and Rindfuss, 2000; Hank, 2001; Lesthaeghe, 2010;

Myrskylä et al., 2011) the context contributing to this variation changes across time and place. Some studies find that economic factors play the key role in fertility variation between urban and rural places (Kulu and Vikat, 2007; Kulu and Washbrook, 2014), while others emphasize the role of sociocultural factors (Hank, 2001; Lois and Becker, 2014; Vitali and Billari, 2017). Some research studies both economic and social factors to gain a better understanding of spatial variation in fertility patterns but few have compared the role of economic and sociocultural factors and none for many countries (Fiori et al., 2014; Hank, 2001; Kulu, 2006; Vitali and Billari, 2017). Clearly, the contexts contributing to the pervasive urban-rural variations are varied and are not well understood on a European level.

Economic determinants of spatial variation in fertility

Economic factors play an important role in individuals' childbearing decisions (Kulu and Washbrook, 2014). The New Home Economics Theory idea of **direct and indirect costs** refers to parenting as a time-intensive role that competes with other career and financial goals (Becker, 1960; Mason, 1997). A quality versus quantity trade-off of childbearing can be applied to urban-rural patterns in fertility. For instance, the large costs of schooling, daily activities, care, and food in an urban center would decrease the incentive to have children – even more so to have large families – and thus may also decrease fertility levels (Becker, 1991). Additionally, higher living costs in urban places may entice young adults to wait until they are financially stable before having a child (Kulu, 2013). This leads to the postponement of childbearing and, ultimately, to smaller family sizes in cities than in rural areas where these costs are lower.

Housing structure and costs also vary spatially. Urban areas tend to have a higher prevalence of apartment-style homes with smaller living spaces. Research demonstrates that individuals living in apartments have lower fertility than those living in single-family homes

(Kulu and Vikat, 2007). The smaller living spaces of apartments may force families to limit childbearing due to space constraints while family-friendly environments, often associated with single-family homes, may facilitate childbearing in rural areas (Felson and Solaun, 1975; Kulu and Vikat, 2007). High housing costs may encourage individuals to move out of urban centers to a rural or suburban setting if they want to have (more) children. These selective moves for fertility intentions may also contribute to patterns of low urban fertility (Kulu, 2013; Kulu and Vikat, 2007; Rusterholz, 2015). However, recent studies show that selective moves from urban centers to family-friendly environments do not drive significant differences in urban-rural fertility levels (Kulu and Washbrook, 2014).

Economic conditions are another possible driver of spatial variations in fertility. Economic development has occurred unevenly between urban and rural areas due to differences in industrialization and other capital advancements. Even in a developed context, the uneven prevalence of natural resources or capital investments may influence fertility levels of local areas differently. Increases in Gross Domestic Product were historically related to declines in fertility but the relationship between economic development and fertility is changing in modern Europe (Myrskylä et al., 2009). Recent work using aggregate level data suggests that the negative relationship between fertility and income has weakened at the national level and has become positive in some sub-national areas (Fox et al., 2019). This suggests that richer regions may have higher fertility; possibly due to changes in family policies, economic interdependence, and migration processes across Europe.

The role of sociocultural factors

Sociocultural factors may contribute to regional variation in fertility levels by influencing individuals living in certain areas. Language was historically used as an indicator of **culture** in Europe (Coale and Watkins, 1986) but, as languages increasingly conformed to national borders over the 20th century, the role of language has become more difficult to interpret and separate from the role of national policies (Klüsener et al., 2013b). The number of **students** in a region is another compositional factor that can be used to understand regional fertility variation. Young adults in higher education tend to postpone childbearing until after finishing their studies. Thus, a region with a larger number of students can be expected to have a negative relationship with fertility levels (Kulu et al., 2007). Other aspects of social context, such as **childcare availability** – a contextual factor – have been linked to increasing levels of fertility and shown to vary considerably within countries (Hank, 2001; Wood and Neels, 2019).

The variation in sociocultural factors across different regional contexts makes it difficult to capture the relationship between these factors and fertility levels across European regions. Nonetheless, it is clear that sociocultural factors play a role in shaping individual-level fertility. There is a large amount of research in psychology and social anthropology that explores the ways in which individuals model, learn from, or otherwise influence one another (e.g. Asch, 1951; Bandura, 1965; Alvergne et al., 2011). Social mechanisms such as peer pressure can act as social controls, leading to new practices or conforming to existing ones (Lesthaeghe, 1980). Prior research demonstrates that individuals within cultural groups, including social classes, behave in similar ways and facilitate the spread of fertility ideals and practices (Klüsener et al., 2019). The general consensus is that individuals in **social groups and networks** influence one another due to similarities stemming from group construction or development (Tajfel, 1981; Hogg and Williams, 2000).

The effect of peer influence on fertility is positive on the individual level – having many friends or other network members with young children increases individuals' fertility (Bühler and Fratczak, 2007; Balbo and Barban, 2014; Lois and Becker, 2014). Lois and Becker (2014) identify three mechanisms that contribute to a social contagion effect on fertility: social learning (about the positives and negatives of childbearing), peer pressure, and decreasing social opportunity costs that can increase or decrease fertility. These social pressures may act unbeknownst to individuals if they are normative.

Normative pressures, or **norms**, can be considered as formalized expectations generated by a community. Norms often stem from social circles and can vary by demographic or socio-economic groups – such as men and women, older and younger cohorts, and educational groups. These are visible at varying levels, demonstrating not only that individuals are influenced by their community but that entire communities can influence other nearby communities. This was central to the spread of the Second Demographic Transition (Lesthaeghe and Neels, 2002) during the latter half of the 20th century which was characterized by a rejection of traditional norms, rise of individualization, and an increase in the importance of economic factors for fertility decisions (Lesthaeghe and van de Kaa, 1986; van de Kaa, 2001). Questions arise as to whether norms are still relevant for fertility behavior in a modern and individualistic society (Udry, 1982) but research on Italy shows a significant positive relationship between the fertility levels of one province and its surrounding provinces (Vitali and Billari, 2017), suggesting that normative factors are important for spatial variation in fertility.

Normative pressures can influence demographic behavior both directly and indirectly. Directly, norms can act through group effects that relate to fertility intentions and attainment (Bühler and Fratczak, 2007; Billari et al., 2009; Lois and Becker, 2014). Indirectly, norms can act through demographic behaviors such as union formation, timing of childbearing, and marriage (occurrence or timing) to influence fertility outcomes. When family-oriented or traditional norms are strong and non-marital fertility is uncommon, a high proportion of married and a low proportion of divorced individuals may be positively related to fertility levels (Easterlin, 1975). A positive relationship between **divorce** and fertility may also arise with increases in nonmarital fertility (Klüsener et al., 2013a) or a high prevalence of repartnering, in which divorced individuals may have additional children (Thomson et al., 2012). Divorce may be negatively related to fertility through expectations of the occurrence, timing, and/or sequencing of family events and desired family structures (Liefbroer and Billari, 2010). Historically, the relationship between divorce and fertility was negative but recent research suggests that the relationship is changing in some countries across Europe to weak or slightly positive (Billari and Kohler, 2004).

The role of space

"Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970) is regarded as the first law of geography. Relationships between two near places can arise from any of the economic, sociocultural, or contextual factors outlined previously. For example, two nearby places are likely exposed to similar economic conditions due to similar geographic environments. It can be hypothesized that one region, adjacent to another with fertile soil, has fertile soil itself. Thus, both regions may have economies dependent on agriculture. Likewise, a region near another with mountainous terrain is unlikely to have an agriculture-based economy. These patterns of economic development are linked to resource availability and are geographically fluid, creating economic similarities in regions exposed to the same geographic conditions.

Individuals can also contribute to these dependencies. As space brings places together, cross-border commuting of populations for work or leisure purposes can create similar conditions. This seems particularly likely in Europe, where the European Union and Schengen areas have contributed to an increase of cross-national worker commuting since their formation (Mathä and Wintr, 2009). By crossing into nearby regions, individuals open themselves to the economic and normative conditions in their destinations, which can influence their fertility at home.

Data and Variables

We use census-adjusted, aggregate-level data for 1,134 NUTS 3 regions across 21 European countries.[2] The NUTS (Nomenclature of Territorial Units for Statistics) classification is a hierarchical system designed by Eurostat to create statistically comparable regions based on existing subnational administrative units and on population size. NUTS 3 units are the smallest of the NUTS units and contain between 150,000 and 800,000 individuals. Larger units include NUTS 2 (between 800,000 and 3 million individuals), NUTS 1 (between 3 million and 7 million individuals), and NUTS 0 (countries).

We use information on the NUTS 3 level because, compared to the next smallest level (NUTS 2), this provides the highest spatial acuity,[3] performs better at separating metropolitan areas from surrounding rural or suburban areas, and thus facilitates the identification of local fertility variation. The boundaries of NUTS 3 regions largely reflect the boundaries of subnational administrative units (districts, counties, provinces, departments, etc.) across most study countries. The level of administrative unit changes by country and may be the first subnational unit (NUTS 3 units represent counties in Lithuania), second subnational unit (NUTS 3 units represent provinces in Italy), or may also represent groups of administrative areas, (NUTS 3 units represent groups of counties in the United Kingdom). We analyze NUTS 3 regions to facilitate demographic comparison, rather than a blend of NUTS levels to facilitate administrative comparisons. The average number of NUTS 3 units per country is 54, with a maximum of 402 (Germany) and a minimum of one (Luxembourg). For all countries, NUTS 3 boundaries conform to the 2013 classification, except for the United Kingdom, which adheres to the 2010 classification. Some islands and other regions isolated from country mainlands are

[2] Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, and the United Kingdom (England and Wales)

[3] For example, Estonia and Lithuania are represented as one NUTS 2 level unit each but classified into five and ten NUTS 3 units, respectively

excluded from the analysis since these regions will have less spatial influence from the closest proximal regions and may display their own patterns of fertility. Appendix A outlines which NUTS 3 regions are omitted from the analyses.

Regional total fertility rate

Our dependent variable is the *Total Fertility Rate (TFR)* measured for each NUTS 3 region. The regional TFR provides an age-standardized indicator of regional fertility, which facilitates cross-contextual comparisons. Data for this fertility indicator come from national statistical offices and cover the year 2010 except for the United Kingdom (2011), Portugal (2011), and France (2009). For eighteen countries, regional TFR is calculated and reported by national statistical offices and published online.[4] For three countries (Belgium, Slovakia, and the United Kingdom), we calculated regional TFR using publicly available information on the number of live births by age of the mother and the size of the female population in each age group.

Determinants of regional TFR

Regional data on the determinants of regional TFR is gathered from Eurostat, the Organization for Economic Co-operation and Development (OECD), and national statistical offices.[5] Population density and the share of apartment housing in a region are used to measure the urban-rural dimension of fertility. *Population density* is calculated by Eurostat for 2010 as the average total population per square kilometer. This measure uses information on land area where available or total area, including bodies of water, where data on land area is not available. In the analyses, we use the natural log of population density to reduce the effect of outliers (e.g. very large metropolitan areas such as London or Paris). To measure *the share of apartment*

[4] See Appendix A, Table A1 for more information on the data sources.
[5] See Appendix A for more information on the data sources.

housing, we use information on conventional dwellings[6] located in residential buildings. We take the ratio of dwellings in buildings with three or more dwellings to total dwellings in all buildings. We use the ratio of dwellings, rather than buildings, to better represent the housing conditions of regions and prevent an underrepresentation of apartment buildings.

To measure the economic determinants of regional fertility, we use information on the Gross Domestic Product (GDP) per capita, employment rate, and the share of employees in agriculture in each NUTS 3 region. *GDP per capita* is expressed as millions of USD in constant prices (constant Purchasing Power Parity) in 2010 per individual for each region. We use the natural log of GDP per capita in the analyses to reduce the effect of outliers and better capture the nonlinear relationship between GDP and TFR. *Regional employment rate* is the ratio of (all) employed persons in a region to the regional population aged 15 to 64 years.[7] We use the square root of employment rate to reduce collinearity between the independent variables. The share of *employees in agriculture* reflects the proportion of employed persons working in agriculture, fishing, and forestry of all employed persons. This variable provides a bridge between economic and spatial factors, since it is expected that regions with a higher share of employees in agriculture are located in rather peripheral rural areas.

To consider the sociocultural determinants of fertility, we use information on the share of divorced individuals in each region.[8] *Share of divorced* is the ratio of individuals aged 15 to 49 years in a region who are divorced in 2011. This measure is calculated using information on individuals who were divorced (the number of ever-divorced individuals was not available) and individuals who were ever married (married, divorced, or widowed). This measure reflects

[6] Conventional dwellings are separate and independent premises, as opposed to collective living quarters, designed for permanent human habitation, with no differentiation between occupied and unoccupied buildings.
[7] For Norway, Switzerland, and the United Kingdom data on the number of employed persons from the national statistical offices was divided by information on the size of the regional population aged 15 to 64 years provided by Eurostat.
[8] Other possible measures of sociocultural factors, such as religion, language, and historical tradition are unfortunately not available at the NUTS 3 level.

the proportion of individuals who divorce and also reflects those who remain divorced. This may lead to an underestimation of the share of divorced individuals if repartnering is common. Information on cohabiting unions and their dissolution is not reported across most countries and so data on cohabiting unions were not included in the analyses. We use the share of divorced individuals to reflect socio-normative forces that are likely to influence the occurrence and persistence (i.e., remaining divorced) of divorce as outlined previously. Table 1 shows the mean and standard deviation of the variables used in the analyses (Appendix B, Table B1 shows these statistics separately for each country).

Methods

Descriptive analyses

We first study variation in total fertility rates across countries using NUTS 3 regions. We examine how regional fertility patterns are clustered together visually across Europe. We then assess the standard deviation of NUTS 3 level TFR from the mean TFR in each country to understand how within-country variation in TFR contributes to patterns in observed fertility rates. We use total fertility rates as standard deviations from mean TFR of the country to focus on how fertility similarities country-specific processes construct patterns across the continent. Last, we explore spatial relationships between each region using Moran's I test for spatial autocorrelation. Moran's I is commonly used to measure spatial dependence among observations. Similarly to other correlation measures, the Moran's I can range from -1 (perfect negative spatial autocorrelation) to +1 (perfect positive spatial autocorrelation). We calculate global Moran's I to test for spatial autocorrelation in all spatial units for each variable of interest. The Moran's I for a given variable is specified as:

$$I = \frac{1}{s^2} \frac{\sum_i \sum_k (y_i - \overline{\mu_y})(y_k - \overline{\mu_y})}{\sum_i \sum_k w_{ik}}$$

and calculated as the difference between the value of variable y in region i and the variable mean μ_y for all neighboring regions k, as prescribed by the spatial weight matrix w, which defines which regions are neighboring (more information on our weight matrix is below in the description of models). The global Moran's I is calculated by summing values across all regions.

Model comparison

We compare five different approaches to estimating regional TFR: Ordinary Least Squares (OLS) regression, two multilevel models, spatial error model, spatial lag model, and spatial autoregressive model with autoregressive error (SARAR). In doing so, we compare model results to identify the shortcomings of the approaches commonly used for spatial analysis, such as OLS and multilevel modeling, and estimate the role of spatial dependence in regional fertility levels. Spatial dependence (or spatial autocorrelation) occurs when the observations (here TFR) of one spatial unit (here NUTS 3 region) are similar and correlated to that of surrounding or nearby units. Spatial dependence causes bias in regression estimates because it violates the assumption that the observations are independent from each other. To compare these models, we only use population density as a covariate to highlight differences between the different modeling approaches; all variables will be incorporated in the final models. All analyses include country fixed effects (or country dummies) to account for between-country differences in fertility levels.

OLS regression estimates the direct effect of regional indicators on fertility levels within the same region. The model is specified as:

$$y_i = \beta x_i + \varepsilon_i$$

where y_i is the estimated TFR in region i, β is the regression coefficient for x (population density) in region i, and ε_i is the error term for the regression equation. This approach does not consider any form of spatial hierarchy or connections between different regions.

Multilevel models incorporate spatial information by nesting smaller spatial units into larger units. These models account for hierarchical spatial relationships between different regions by considering that smaller spatial units within the same larger units are more similar to each other than to spatial units in other larger units. We estimate two sets of multilevel models. In the first analysis, NUTS 3 regions are nested in the larger NUTS 2 subnational regions. In the second analysis, NUTS 3 regions are nested within countries. The multilevel model is specified as:

$$y_i = \beta x_i + u_j + \varepsilon_i$$

where y_i is the estimated TFR in region i, β is the regression coefficient for population density (x) in region i, u_j is the error term for unit j (NUTS 2 or country) and ε_i is the error term for the lowest spatial unit (NUTS 3). Although these methods account for some degree of spatial dependence between different regions, they are only reflective of administrative boundaries and do not account for relationships between regions that occur across regional or national boundaries nor due to proximity.

Spatial regressions account better for proximity of neighboring spatial units than multilevel models. The spatial error, spatial lag, and spatial autoregressive models all utilize information from spatially-weighted neighboring regions to predict regional TFR. Accounting for the interrelationship between neighboring regions is important, given the high level of spatial autocorrelation in regional total fertility rates and social interactions between adjacent regions that can facilitate the spread of ideas, norms, and behaviors (Watkins, 1991). Our spatial models employ a first order queen contiguity approach to spatial weights. This approach assigns a binary spatial weight to any adjacent region to reflect contiguity. Weights are then row-standardized (standardized within each region) in the weight matrix. For example, if a region is adjacent to five others then it will have five links in the weight matrix which each link getting a weight of one divided by number of neighbors (in this case five). There are 5,891 regional connections and an average of 5.2 connected neighbors, or links, per region using this method. We choose the contiguity approach here, rather than a distance-based approach, due to the unequal sizes of our spatial units that would lead to unequal representation of spatial connections. The spatial error model accounts for spatially lagged errors from neighboring region estimations. This model assumes the presence of autocorrelation and the strength and significance of the spatial error term (λ) reflects the spatial dependence of the estimation errors and measures the average influence of estimation errors from neighboring regions on the fertility levels of region *i*. The spatial error model is specified as:

$$y_i = \beta x_i + \lambda \sum_{k=1}^{N} w_{ik}\varepsilon_k + \xi_i$$

where y_i is the estimated TFR in region *i*, λ is the spatial error term, *k* denotes the neighboring regions, w_{ik} refers to the spatial weight matrix, and ε_k refers to the regression error from neighboring regions *k* which are summed across all neighboring regions.

The spatial lag model accounts for spatially lagged TFR from connected neighboring regions, as determined by the first order queen matrix. This model does not assume spatial dependence in the same way as the error model. This model uses the spatially lagged TFR (ρ) as a predictor of fertility in a given region to identify effects of spatial spillover from the dependent variable. In other words, the TFR of neighboring regions is taken into account when estimating fertility levels of a given region. The strength and significance of the spatial lag term reflects the presence and strength of spatial dependence in regional data and measures the summative association of TFR in neighboring regions with fertility levels in region *i*. The spatial lag model is specified as:

$$y_i = \beta x_i + \rho \sum_{k=1}^{N} w_{ik} y_k + \varepsilon_i$$

where y_i is the estimated TFR in region *i*, ρ is the spatial lag term, *k* denotes the neighboring regions, w_{ik} refers to the spatial weighting of neighboring region *k* for estimated region *i,* and y_k is the TFR of the neighboring region which are summed across all neighboring regions *k* assigned by the weight matrix.

Lastly, the spatial autoregressive model with autoregressive error (SARAR) combines the spatial error and spatial lag models. The SARAR model accounts for assumed spatial dependence by including spatially lagged errors from neighboring regions, similar to the spatial error model. The SARAR model also identifies spatial spillover by including a spatially lagged dependent variable, similar to the spatial lag model. The SARAR model is specified as:

$$y_i = \beta x_i + \rho \sum_{k=1}^{N} w_{ik} y_k + \lambda \sum_{k=1}^{N} w_{ik} \varepsilon_k + \xi_i$$

where y_i is the estimated TFR in region *i*, *k* denotes the neighboring regions, ρ is the spatial lag term, λ is the spatial error term, and w_{ik} refers to the spatial weight assigned to region *k* for estimated region *i*.

Spatial lag analysis

We proceed with using a spatial lag regression to demonstrate how multi-dimension analysis can be included in one spatial framework. We estimate stepwise models to assess the relative importance of economic, sociocultural, and spillover factors in regional fertility levels. The first step estimates regional TFR adjusting for spatial determinants – population density and share of apartment housing and spatially lagged fertility. Then, we include economic determinants – GDP per capita, employment rate, and proportion of employed persons working in agriculture – to understand whether and how economic factors influence spatial patterns of fertility. Last, we add sociocultural determinants – the share of divorced individuals – to understand whether and how these factors influence spatial patterns of fertility when spatial and economic factors are adjusted for. Due to varying measurement scales of the independent variables, it is difficult to compare the magnitude of the coefficients. Therefore, we also present standardized beta coefficients, which express differences in standard deviations from the mean of the given independent variable.

Results

Descriptive analyses

Figure 1 shows the total fertility rate in NUTS 3 regions in 2010 across 21 European countries. The continental bifurcation trend is evident in the total fertility rates on a local level. This is clearly seen in the differences across national borders, such as the France-Germany border, which separates a high-fertility and a low-fertility country. One could assume fertility in regions along this border would be similar to each other due to geographic proximity but this is not the case, as regions along this border display quite different levels of fertility. Patterns like this across the continent support research identifying the important role of nations in shaping fertility differences (Klüsener et al., 2013b). However, not all borders are as distinct in separating fertility patterns. NUTS 3 level TFR's are similar across some national boundaries, for example across the Portugal-Spain, Germany-Poland, and Belgium-France borders. These examples suggest that borders are not as strong in separating fertility patterns within fertility regimes (e.g. between high and high fertility countries) as they are across regimes (e.g. between high and low fertility countries) and that geographic connections between regions may be important for some fertility patterns.

Figure 1 also overlays the boundaries of NUTS 2 regions on the map to identify variations in local fertility rates within the larger NUTS 2 regions used in prior research (Basten et al., 2011; Klüsener et al., 2013a; Fox et al., 2019). There is variation in fertility rates within NUTS 2 regions but this variation is larger in some NUTS 2 regions than in others. Local variation is present in larger NUTS 2 units, such as those in France and Spain, and also in smaller regions in countries, such as Germany and the Netherlands. Variation is most notable within NUTS 2 regions where an urban region is surrounded by suburban or rural regions. Urban-rural variation is not limited to major or capital cities but is demonstrated across Europe for urban centers of varying population levels, such as Paris in the French Île-de-France region and Lódz in the Polish Lódzkie region.

To better understand within-country variation in the TFR, Figure 2 shows the standard deviation of NUTS 3 level total fertility rates from the mean TFR in the given country. Again, Figure 2 overlays the boundaries of countries and NUTS 2 regions to demonstrate relative local variation. Overall, the local variation becomes more evident in Figure 2. Regions where the TFR seems similar in Figure 1 become more distinct in Figure 2. For instance, while Swedish NUTS 3 regions seem to have similar levels of fertility in Figure 1, the subnational diversity becomes clear in Figure 2. Again, this pattern is prevalent both in countries with larger NUTS 2 regions and in countries with smaller NUTS 2 regions. Figure 2 demonstrates how similar TFR's across national borders can be created by below-average fertility for one country but above-average fertility for the other. For instance, across the Italy-Switzerland or Germany-Poland borders. This suggests spatial proximity mechanisms, rather than country-specific mechanisms, can contribute to fertility similarities between regions in different countries. For instance, values of above-average fertility in East Germany reflect similar TFRs to below-average values in Poland. Again, spatial proximity mechanisms appear to more important for cross-national fertility similarities for regions within the same fertility regime than regions in separate fertility regimes.

The role of geographic proximity is further supported by the Moran's I coefficients. We would expect coefficient values of zero if no autocorrelation was present. Table 2 demonstrates the Moran's I statistics for all analyzed variables and shows ubiquitous and significant spatial clustering across the sample. The value of the Moran's I statistic for the TFR is 0.84 ($p < 0.001$), indicating a strong spatial autocorrelation – the strongest of all variables used in the analysis. The strong presence of spatial autocorrelation will also inform our model choice in model comparisons.

Model comparison

Table 3 shows the results of comparing different approaches to estimating regional TFR. As previously mentioned, the only independent variables in these models are (the natural log of) regional population density and country fixed effects. Table 3 begins with the nonspatial OLS estimation method, adds spatial information using multilevel modeling, then includes three approaches to spatial modeling techniques. In all models, population density has a significant and negative relationship with regional TFR; fertility is lower in regions with high population density. This is consistent with prior literature. The magnitude of the coefficient for population density does not vary considerably between models but is different between the models as they account for different aspects of space (hierarchical organization, dependence, spillover, or both). The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) follow a similar trend of decreasing values as we move from nonspatial to spatial models and suggest that multilevel spatial information is not as useful for model fit as spatially weighted information. Including multilevel spatial information reduces model fit compared to the OLS approach but including a spatial error or lag term greatly increases model performance. The differences in AIC and BIC suggest that this approach to modeling space is better for model quality than multilevel approaches. The difference in AIC and BIC between the OLS and multilevel country models indicates a multilevel model with NUTS 3 regions nested in countries or NUTS 2 units do not fit as well as an OLS model with country fixed effects.

The Moran's I coefficients in Table 3 are calculated in a similar way to what we have shown before except that here we calculate them for the residuals of the regression models, rather than the observed values of the variables. The Moran's I of the residuals reflects the presence of spatial autocorrelation within the model estimates and, thus, the presence of bias. As we move from nonspatial to spatial models, the spatial autocorrelation of the residuals decreases and becomes insignificant. The Moran's I value is strongest in both magnitude and significance for the OLS regression and country multilevel model, indicating that only controlling for the country level is insufficient and likely to produce biased estimates due to spatial autocorrelation. The multilevel model in which NUTS 2 regions are the higher-level units has much smaller autocorrelation, but the Moran's I value remains significant. Only the spatial models eliminate spatial autocorrelation in the model residuals. The spatial error and lag terms in the three spatial models both indicate that spatial dependence from neighboring regions play a significant role in predicting the fertility levels of a given region. The spatial error model shows that an increase in the estimation error of neighboring regions is strongly associated with an increase in regional fertility levels. The spatial lag model shows that an increase in the fertility levels of neighboring regions is strongly associated with an increase in regional fertility levels. The SARAR model shows that the inclusion of both spatial error and lag terms reduces the effect of both terms compared to the Spatial Error and Spatial Lag models, in which they are included individually. The SARAR model also shows that, when both are considered in the model, spatially lagged error and spatially lagged fertility are significantly related to regional TFR.

From Table 3, we conclude that the spatial models (spatial error, spatial lag, and SARAR) are the most appropriate for estimating regional fertility across Europe. These models provide a much better fit than nonspatial models (OLS, multilevel (country), and multilevel (NUTS 2)) and eliminate spatial autocorrelation that biases other coefficient estimates. The main difference between these spatial models is conceptual. Spatial error models emphasize the spatial interdependence between regression error terms and are interpreted similarly to OLS and multilevel models. Spatial lag and SARAR models measure spatial spillover effects and thus their coefficients need to be interpreted differently (Golgher and Voss, 2016). One example of this is seen in the difference of the model intercepts with spatial spillover (spatial lag, SARAR) and intercepts without spatial spillover (OLS, multilevel country, multilevel NUTS 2, spatial error).

Using models with more variables highlights the differences in coefficient estimation that can occur between approaches (Table 4). Including more variables yields larger differences in variable coefficients but the trends in Moran's I and model fits remain the similar to Table 3. The spatial (spatial error, spatial lag, and SARAR) models provide better model fit than the nonspatial (linear, multilevel country, and multilevel NUTS 2) models but the difference between the spatial models is not large. Table 4 also shows how choice of modelling approach can influence statistical significance of coefficient relationships, since the inclusion of spatially lagged error leads to a significant relationship between housing and fertility.

In the remainder of the analysis we will estimate spatial lag models because we are interested in the spatial interrelationships between fertility levels across regions and how fertility spillover is related to regional fertility levels. We choose the spatial lag model over the SARAR model, which also includes information on spatial spillover. Both models resolve bias from spatial autocorrelation but the spatial lag provides the most efficient estimates and theoretical simplicity in model estimation (Anselin and Bera, 1998).

Spatial lag analysis

Table 5 shows the results of stepwise regression using spatial lag models. All models control for country fixed effects to account for large differences in country-level TFR and other exogenous differences. First, we include the spatial determinants of regional fertility. Population density is negatively related to regional TFR, showing that more densely populated regions have lower fertility, as we would expect (Model 1). Next, we include the share of apartment housing in a region in the model (Model 2). This variable has a significant negative relationship with regional fertility; larger shares of apartment housing in a region are related to lower levels of TFR. Interestingly, introducing this determinant into the model explains away the initial relationship of regional population density with fertility. This is likely because both measures account for urbanization. In both Model 1 and Model 2, the spatially lagged fertility term (ρ) is significant and positive, indicating that there is a significant spatial dependence of regional fertility on the fertility of neighboring regions. Thus, high surrounding regional fertility is related to higher fertility within a given region.

In Model 3, we introduce economic factors: GDP per capita, employment rate, and the proportion of persons employed in agriculture. Of the economic factors, GDP per capita is the only significant predictor that is related to regional fertility. GDP has a significant and negative relationship with regional TFR; higher regional GDP per capita is associated with lower levels of regional fertility. The coefficient of the share of apartment housing slightly decreases with the inclusion of economic variables in the model.

In Model 4, we introduce sociocultural aspects of fertility, as measured by the share of divorced individuals. A higher regional share of divorced is associated with a significantly lower regional TFR. Thus, regions with a higher ratio of population which is divorced can be expected to have lower fertility. The introduction of the share of divorced persons in the model further reduces the magnitude and significance of the coefficients of economic determinants and the coefficient of the share of apartment housing becomes insignificant. This indicates a stronger overall relationship between sociocultural factors and fertility than economic factors and fertility across European regions when both are accounted for. This pattern remains the same when insignificant variables are removed from the model, and only population density, GDP per capita, and the share of divorced individuals are considered (see Appendix B, Table B2). Lastly, the AIC value decreases with the inclusion of the share of divorced, indicating that Model 4 provides the best relative fit for predicting regional TFR.

The difference in the magnitude of the coefficients of the share of divorced and GDP per capita is likely due to the different scale of measurement of these predictors. Model 5 shows the results of Model 4 but in a different form by displaying standardized regression coefficients[9]. These coefficients facilitate the comparison of the strength of the relationship between regional fertility and its determinants. GDP per capita, share of divorced, and the rho term (not standardized) remain significantly related to regional fertility. Standardizing the determinants increases the magnitude of the coefficient of GDP and decreases that of the share of divorced due to their difference in measurement scales. Standardized coefficients demonstrate a stronger relationship between divorce and fertility than GDP per capita and fertility but the difference between the coefficients is not large. This indicates that, while regional share of divorced has a stronger relationship with fertility, both factors are important for determining fertility levels.

[9] The ρ coefficient is a product of the spatial lag model and is not standardized in Model 5.

Discussion and Conclusion

This study investigated regional fertility variation across Europe using small, comparable (NUTS 3) spatial units. This is the first study to use such small-scale geographical units to study spatial variation and dependence in fertility across Europe. We also compared the performance of common nonspatial approaches with spatial approaches for studying regional variation in fertility levels in high spatial detail. We moved beyond previous research by demonstrating spatial models and examining the relative importance of economic and sociocultural factors in spatial fertility variation under one framework.

We showed a significant spatial variation in TFR across Europe. Interestingly, we observed similar levels of fertility between some regions that are geographically close but separated by national borders (and thus likely adhere to different family policies). This trend is stronger for countries of the same bifurcation group than countries of different bifurcation groups. Similar levels of fertility across national boundaries are interesting to note, as different country-specific patterns can create similar levels of fertility. For instance, adjacent regions in Brandenburg in east Germany and Lubuskie in west Poland have similar levels of TFR but this is above-average for Germany and below-average for Poland. Cross-border similarities support the argument that the role of national borders in fertility variation may be decreasing and regional boundaries may become increasingly important (Klüsener et al., 2013a). While variation across local units persisted throughout Europe, issues of spatial dependence in the units also occurred throughout the studied countries.

We showed that multilevel models that nest spatial units within larger administrative units, commonly used approaches, do not resolve issues of spatial autocorrelation on the NUTS 3 level that bias model results. Only the spatial (lag, error, and SARAR) models resolve issues of spatial autocorrelation by including spatial autocorrelation terms in the regression model. We conclude that each spatial model yields different coefficient results and that the choice of the method is largely theoretical. It is clear that differences between spatial models increase as more variables are included in the model but our conclusions remain the same. While one may expect better model fit by including two spatial terms, as opposed to one, we see that this is not the case and there are minor differences in model fit between the spatial models. We encourage the use of spatial modeling in fertility research for accurate coefficient estimates but urge theoretical consideration in model selection for informative results.

Analysis of the aspects relevant for understanding local fertility variation showed that GDP per capita, the share of divorced individuals, and spatially lagged fertility were the main factors related to regional TFR. These factors had strong and significant relationships with regional fertility that were independent from other variables in the model. This supports the view that all three realms of fertility determinants – spatial, economic, and sociocultural – are relevant in a single framework for understanding modern fertility variation. Comparing the standardized regression coefficients revealed that the relationship between sociocultural and marriage factors and local fertility is important across Europe at a magnitude greater than that of economic factors. These findings shed light on the relative magnitude of relationships between economic and sociocultural factors and fertility across Europe but do not clarify how these relationships are changing over time. Whereas repartnering or nonmarital fertility may contribute to a positive relationship between fertility and the share of divorced persons, we find a negative relationship. The negative relationship supports our interpretation that the share of divorced individuals reflects the disruptive effects of divorce on family formation events but also cultural differences between regions. The persistence of the spatially lagged fertility term highlights that spatial relationships between places need to be considered by fertility researchers to understand modern fertility trends, hopefully with new data with higher spatial acuity.

This is the first pan-European study that analyses information on small standardized spatial units. It is always a question in spatial analysis what spatial scale to use. We believe that the NUTS 3 level is the most ideal for our analysis and for cross-sectional comparison across countries. The definition of spatial units plays an important role in analysis results and the use of other spatial levels creates additional issues such as the Modifiable Areal Unit Problem (MAUP), which means that analytical results are sensitive to the definition of the spatial units. Spatial dependency may also change with unit specification. We may find less spatial dependency utilizing larger spatial units if regional trends play a more important role. Utilizing smaller spatial units, we may find more or less spatial dependency, depending on how meaningful the units are in terms of administrative or social groups. Using smaller units, as increasingly possible with advances in spatial data accuracy, would require more information on migration and commuting zones to develop informative units.

This research makes two compromises: utilizing general indicators, for instance the share of divorced individuals as the only sociocultural indicator and examining a cross-section of fertility. These compromises reflect our preference for high spatial detail in the analyses. Although our sociocultural measure was crude, we believe it to be a good proxy for the sociocultural factors and find that it is strongly and negatively related to regional fertility levels. More detailed data covering a longer time period and more detailed indicators would warrant a better understanding of European local fertility variation and how variation changes over time. Furthermore, greater insight into the relative importance of economic and sociocultural factors in local fertility can be created by employing context-specific sociocultural determinants. Recent advances in data with high spatial accuracy will hopefully inform future research without compromising between the types of determinants used and spatial accuracy. Future data availability may also facilitate individual-level analysis with high spatial acuity.

A preference for high spatial detail in the analyses also led us to omit some important determinants of regional fertility. Such determinants include both internal and international migration, and gender equality. Whereas internal migrants moving from urban to rural areas for childbearing are not captured, they are also not expected to have a large effect on the results (Kulu and Washbrook, 2014). International immigrants are also important and tend to move to urban centers, where they may have higher fertility levels than natives, particularly directly after migration (Kulu et al., 2007; Milewski, 2007). Accounting for migrants is expected to increase differences between urban and rural areas. Additionally, gender equality is linked to national and regional fertility increases across Europe (Brewster and Rindfuss, 2000; McDonald, 2000; Myrskylä et al., 2009). Including gender equality in the analysis may further explain relationships between both economic and sociocultural determinants and regional fertility, providing a better picture of European patterns. However, measures of internal and international migration, and/or gender equality are not available at the NUTS 3 level across the study countries.

Nonetheless, this study demonstrated the advantages of using data on such a small spatial scale and for so many countries across Europe. We studied fertility variation across Europe and provided a discussion of meaningful ways to account for common modeling issues when using aggregate level data. We showed that variation between NUTS 3 fertility rates arises as a combination of economic, sociocultural, and spatial factors and that patterns of variation, such as between urban and rural places, are persistent across Europe during a period of high variability in fertility. The persistence of geographic variation will be important to understand fertility levels across Europe as they continue to change and as European fertility bifurcation groups converge (Jalovaara et al., 2019). Understanding how spatial variation of fertility is constructed over time will allow future studies to further understand the ongoing processes evident in this research.

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Table 1. Descriptive Statistics of NUTS 3 regions (N = 1,134)

Variable	Mean	Standard Deviation
Total fertility rate	1.57	0.29
Population density (per km^2)	512	1,133
Share of apartment housing	0.44	0.19
GDP per capita (millions USD)	0.28	0.35
Employment rate	0.69	0.17
Proportion of persons employed in agriculture	0.05	0.06
Share of divorced individuals	0.13	0.04

Source: national statistical offices, Eurostat, OECD, author calculations

Table 2. Results of global Moran's I tests (N = 1,134)

Variable	Observed value	P value
Total fertility rate	0.84	0.0000
Population density	0.38	0.0000
Share of apartment housing	0.43	0.0000
GDP per capita	0.19	0.0000
Employment rate	0.14	0.0000
Proportion of persons employed in agriculture	0.65	0.0000
Share of divorced individuals	0.77	0.0000

Source: national statistical offices, Eurostat, OECD, author calculations

Table 3. Comparing the results of five different regression methods, using only population density as a predictor (N = 1,134)

	OLS	Multilevel (Country)	Multilevel (NUTS 2)	Spatial Error	Spatial Lag	SARAR
Intercept	1.5019 *** (0.0254)	1.6850 *** (0.0640)	1.5328 *** (0.0349)	1.5592 *** (0.0330)	0.8274 *** (0.0502)	1.2123 *** (0.1082)
Population Density (log)	-0.0116 *** (0.0034)	-0.0117 *** (0.0034)	-0.0192 *** (0.0035)	-0.0184 *** (0.0035)	-0.0128 *** (0.0030)	-0.0163 *** (0.0034)
Spatially lagged error (λ)				0.5346 *** (0.0316)		0.3369 *** (0.0757)
Spatially lagged TFR (ρ)					0.4722 *** (0.0303)	0.2235 ** (0.0703)
Moran's I^{+}	0.2952 ***	0.2971 ***	0.0835 ***	-0.0201	0.0155	-0.0131
AIC	-1513.2	-1415.8	-1507.7	-1711.6	-1710.6	-1715.1
BIC	-1402.5	-1395.6	-1386.9	-1595.8	-1594.8	-1594.3

Source: national statistical offices, Eurostat, OECD, author calculations
Notes: Models (except for 'Multilevel (Country)') controlled for country fixed effects; * p < 0.05, ** p < 0.01, *** p < 0.001; $^{+}$ Moran's I refers to the spatial autocorrelation of model residuals

Table 4. Comparing the results of five different regression methods, using full model (N = 1,134)

	Linear	Multilevel (Country)	Multilevel (NUTS 2)	Spatial Error	Spatial Lag	SARAR
Intercept	1.5592 ***	1.7288 ***	1.5332 ***	1.5862 ***	0.9171 ***	1.5082 ***
	(0.0597)	(0.0832)	(0.0628)	(0.0588)	(0.0671)	(0.1080)
Population Density	-0.0087 #	-0.0086	-0.0007	0.0074	-0.0050	0.0063
	(0.0053)	(0.0052)	(0.0057)	(0.0058)	(0.0046)	(0.0057)
Proportion of apartment housing	-0.0492	-0.0548	-0.1549 ***	-0.1572 ***	-0.0541	-0.1483 ***
	(0.0382)	(0.0379)	(0.0408)	(0.0417)	(0.0338)	(0.0416)
Gross Domestic Product per capita	-0.0195 **	-0.0189 **	-0.0044	-0.0053	-0.0106 #	-0.0056
	(0.0061)	(0.0061)	(0.0061)	(0.0055)	(0.0054)	(0.0055)
Employment rate	0.0066	-0.0055	0.1005 #	-0.0138	-0.0621	-0.0204
	(0.0583)	(0.0584)	(0.0563)	(0.0528)	(0.0516)	(0.0534)
Proportion of employed persons in agriculture	-0.1060	-0.1198	-0.1202	-0.0103	-0.0414	-0.0109
	(0.1058)	(0.1056)	(0.1042)	(0.1036)	(0.0933)	(0.1037)
Share of divorced individuals	-0.5154 **	-0.4806 *	-0.7324 ***	-0.5967 **	-0.4448 **	-0.5759 ***
	(0.1889)	(0.1873)	(0.2109)	(0.2065)	(0.1668)	(0.2044)
Spatially lagged error (λ)				0.5619 ***		0.5190 ***
				(0.0306)		(0.0566)
Spatially lagged TFR (ρ)					0.4729 ***	0.0547 ***
					(0.0301)	(0.0652)
Moran's I^{+}	0.2977 ***	0.2999 ***	0.0773 ***	0.0204	-0.0263	-0.0248
AIC	-1536.3	-1415.2	-1520.6	-1752.0	-1734.9	-1750.4
BIC	-1400.4	-1369.9	-1374.6	- 1611.1	-1593.9	-1604.4

Source: national statistical offices, Eurostat, OECD, author calculations

Notes: Models (except for 'Multilevel (Country)') controlled for country fixed effects; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; $^{+}$ Moran's I refers to the spatial autocorrelation of model residuals

Table 5. Results of Stepwise Spatial Lag Regressions (N = 1,134)

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.8274 ***	0.8087 ***	0.8512 ***	0.9171 ***	0.7764 ***
	(0.0502)	(0.0491)	(0.0626)	(0.0671)	(0.0474)
Population Density (log)	-0.0128 ***	-0.0003	-0.0025	-0.0050	-0.0067
	(0.0030)	(0.0043)	(0.0046)	(0.0046)	(0.0063)
Share of apartment housing		-0.1135 ***	-0.0930 **	-0.0541	-0.0105
		(0.0278)	(0.0306)	(0.0338)	(0.0066)
GDP per capita (log)			-0.0121 *	-0.0106 #	-0.0100 #
			(0.0054)	(0.0054)	(0.0051)
Employment rate (sqrt)			-0.0597	-0.0621	-0.0058
			(0.0518)	(0.0516)	(0.0048)
Proportion of persons employed in agriculture			0.0003	-0.0414	-0.0024
			(0.0923)	(0.0933)	(0.0055)
Share of divorced individuals				-0.4448 **	-0.0191 **
				(0.1668)	(0.0072)
Spatially lagged TFR (ρ)	0.4722 ***	0.4776 ***	0.4743 ***	0.4729 ***	0.4729 ***
	(0.0303)	(0.0300)	(0.0301)	(0.0302)	(0.0302)
AIC	-1710.6	-1725.2	-1729.8	-1734.9	-1734.9
BIC	-1594.8	-1604.4	-1593.9	-1593.9	-1593.9

Source: national statistical offices, Eurostat, OECD, author calculations
Notes: Models controlled for country fixed effects; # $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; + Moran's I refers to the spatial autocorrelation of estimate residuals

Figure 1. Observed 2010 Total Fertility Rates of NUTS 3 regions. Source: National Statistical Offices, author calculations.

Figure 2. Standard Deviations of 2010 NUTS 3 Total Fertility Rates from Country Mean TFR. Source: National Statistical Offices, author calculations.

Appendix A – Further description of data

NUTS 3 regions

Analyses are conducted using the 2013 NUTS 3 boundary classifications. The 2013 boundaries were chosen as this is the most current classification, most data are reported along 2013 boundaries, and these adhere to the 150,000 to 800,000 population thresholds. Data for the United Kingdom adheres to 2010 NUTS 3 boundaries due to data availability constraints. There are no major differences between the 2010 and 2013 boundaries for the United Kingdom, except for London regions which experienced a change from 5 to 21 regions, respectively.

Where data is published along 2010 NUTS boundaries, an aggregation method was used to derive data along the 2013 boundaries. Where this was not possible, an areal interpolation method (Goodchild et al., 1980) was used to classify data along 2013 boundaries. This method uses a count density approach, assumes an equal dispersion of persons across each region, and does not account for population clustering. Interpolated estimates were compared to non-interpolated values within the same country and lie within +/- 1.5% of the original counts for non-interpolated regions.

Table A1. Data Sources by Country

Country	NUTS 3 Units (n)	Year (TFR)	Source (TFR)	Access Date
Austria	35	2010	http://www.statistik.at	4 April 2018
Belgium	44	2010	Personal liaison	1 June 2018
Czech Republic	14	2010	https://www.czso.cz	13 April 2018
Denmark	11	2010	http://www.statbank.dk	18 June 2018
Estonia	5	2010	http://pub.stat.ee	4 June 2018
Finland	19	2010	http://pxnet2.stat.fi	4 April 2018
France	96	2009	https://www.epsilon.insee.fr	2 April 2018

Germany	402	2010	http://www.inkar.de	30 March 2018
Hungary	20	2010	Personal liaison	17 April 2018
Italy	110	2010	http://demo.istat.it	2 April 2018
Lithuania	10	2010	https://osp.stat.gov.lt	4 April 2018
Luxembourg	1	2010	http://www.statistiques.public.lu	17 July 2018
Netherlands	40	2010	Personal liaison	4 May 2018
Norway	19	2010	https://www.ssb.no	4 April 2018
Poland	72	2010	https://bdl.stat.gov.pl	9 April 2018
Portugal	23	2011	https://www.ine.pt	18 July 2018
Slovakia	8	2010	http://statdat.statistics.sk	18 July 2018
Spain	47	2010	http://www.ine.es	2 April 2018
Sweden	21	2010	http://www.statistikdatabasen.scb.se	4 April 2018
Switzerland	26	2010	https://www.bfs.admin.ch	9 May 2018
United Kingdom (England and Wales)	111	2011	https://www.ons.gov.uk	6 July 2018

NUTS 3 regions omitted from analyses

Some NUTS 3 regions were omitted from the analyses due to concerns of fertility patterns and spatial relationships with the rest of the sample. Omitted regions of Spain include the Balearic Islands (1.35 TFR), Canary Islands (1.11 TFR), Cueta (1.82 TFR), and Mellila (2.47 TFR). Omitted regions of France include the overseas departments (2.43 TFR) of Guadaloupe, Matrinique, Guyane, La Reunion, and Mayotte. Omitted regions of Portugal include the autonomous regions of Azores (1.45 TFR) and Madiera (1.27 TFR).

Sources of data on the fertility covariates

Regional population density is calculated by Eurostat (Eurostat table "demo_r_d3dens"). The counts of apartment housing is also derived from Eurostat (Eurostat table "cens_11dwob_r3"). Data on employment rates is derived from Eurostat data on employed persons (Eurostat table "nama_10r_3empers") and regional populations (Eurostat table "demo_r_pjanaggr3"). Employment data is not available from Eurostat for Norway, Switzerland, and the United Kingdom. For these countries, employment data was downloaded from respective national statistical offices, then calculated using the number of employed persons and Eurostat data on the size of the regional population aged between 15 and 64 years. Data on the proportion of employed persons in agriculture was calculated in a similar manner. Eurostat data (Eurostat table "cens_11ms_r3") on employed persons by NACE activity were used for calculations for all countries except Norway, Switzerland, and the United Kingdom. Data on the share of divorced individuals is derived from Eurostat data on regional populations by marital status (Eurostat table "cens_11ms_r3").

Data on Gross Domestic Product is derived from OECD data on regional indicators on the TL3 level (OECD table "Regional GDP"). The OECD TL3 typology for the OECD are equivalent to the NUTS 3 regions of Eurostat for all regions except Belgium, Germany, and the United Kingdom. Due to data limitations for TL3 regions, the GDP of Belgian and German regions is reported by the OECD for the Eurostat NUTS 3 regions. For the United Kingdom, OECD data is reported on 2013 NUTS 3 regions. GDP values for 2010 NUTS 3 regions were calculated by aggregating the 2013 regions.

Appendix B – Further tables and results

Table B1. Variable means and standard deviations by country

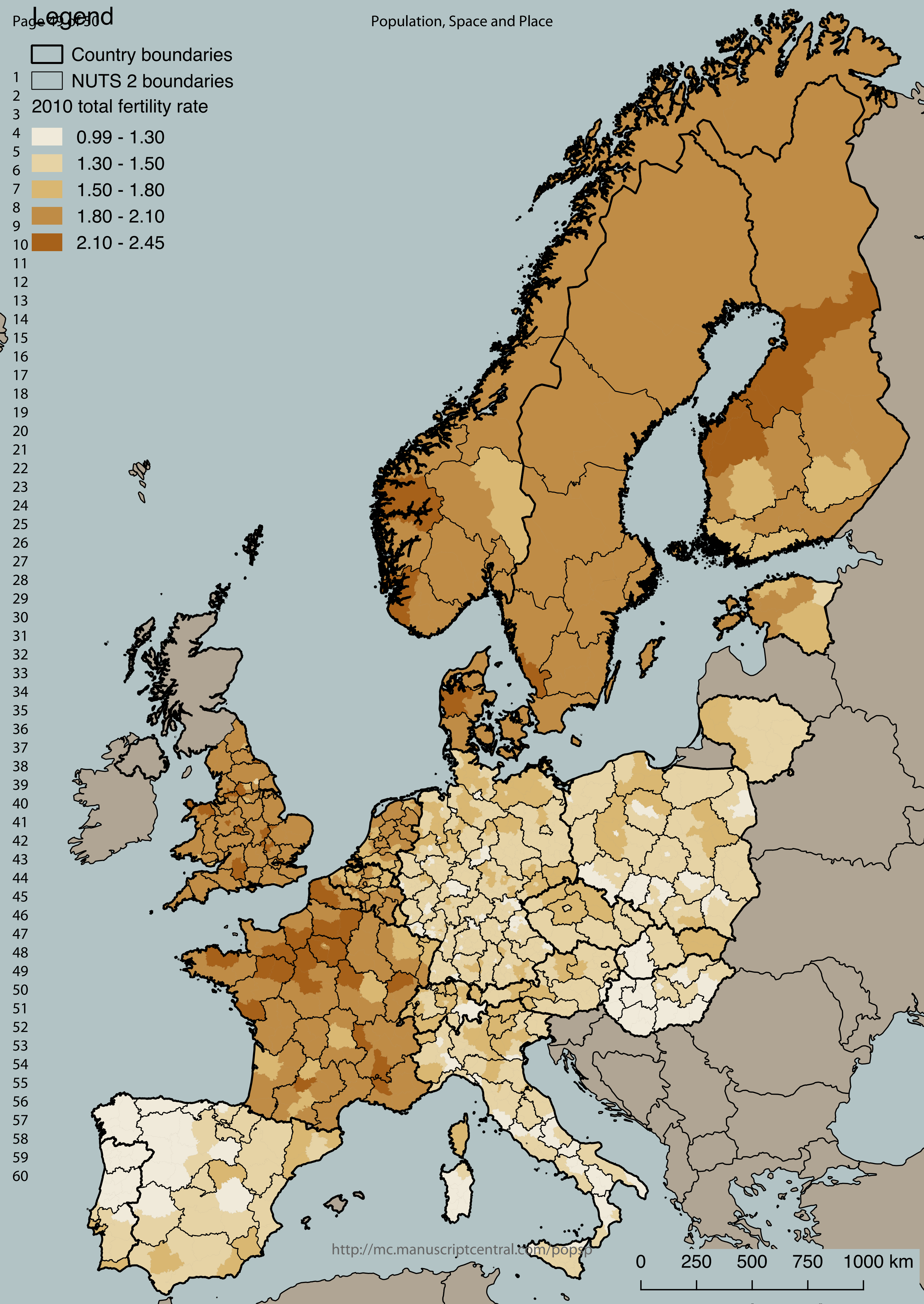
Country	TFR	Population density	Housing ratio	GDP per capita	Employment ratio	Agriculture ratio	Share of divorced
Austria	1.45 (0.11)	220.0 (714.1)	0.3916 (0.1771)	0.4374 (0.4778)	0.7177 (0.1117)	0.0897 (0.0519)	0.1355 (0.0259)
Belgium	1.84 (0.11)	503.3 (1014.6)	0.1908 (0.1499)	0.3548 (0.2520)	0.5614 (0.1181)	0.0270 (0.0204)	0.1636 (0.0247)
Switzerland	1.52 (0.12)	483.7 (1009.8)	0.5866 (0.1449)	0.7362 (0.8345)	0.6656 (0.0709)	0.0498 (0.0299)	0.1182 (0.0175)
Czech Republic	1.49 (0.06)	297.8 (645.7)	0.5472 (0.1379)	0.05420 (0.0186)	0.6699 (0.1114)	0.0369 (0.0194)	0.2046 (0.028)
Germany	1.42 (0.10)	521.6 (678.7)	0.4673 (0.1929)	0.4406 (0.4183)	0.7582 (0.211)	0.0236 (0.0206)	0.1348 (0.0273)
Denmark	1.96 (0.13)	597.9 (1144.9)	0.3851 (0.2015)	0.2123 (0.3002)	0.7478 (0.1108)	0.0286 (0.0208)	0.1506 (0.0191)
Estonia	1.71 (0.2)	45.1 (48.9)	0.6602 (0.1677)	0.1209 (0.0434)	0.5705 (0.0741)	0.0573 (0.0402)	0.2390 (0.0106)
Spain	1.34 (0.16)	121.3 (169.6)	0.5565 (0.1647)	0.1097 (0.1039)	0.6060 (0.0788)	0.0722 (0.0463)	0.0897 (0.0166)
Finland	1.95 (0.20)	28.9 (35.8)	0.5156 (0.0962)	0.3902 (0.5410)	0.6904 (0.079)	0.0691 (0.0286)	0.1632 (0.0207)
France	1.99 (0.15)	558.9 (2470.3)	0.3465 (0.177)	0.1169 (0.0861)	0.6188 (0.0881)	0.0455 (0.0304)	0.1272 (0.0169)
Hungary	1.24 (0.11)	250.0 (716.2)	0.3215 (0.1413)	0.0605 (0.0243)	0.5100 (0.1467)	0.1046 (0.044)	0.2025 (0.02)

Italy	1.37 (0.13)	263.0 (367.2)	0.5733 (0.1348)	0.1503 (0.0996)	0.6150 (0.105)	0.0569 (0.0441)	0.0460 (0.0182)
Lithuania	1.49 (0.06)	46.5 (23.7)	0.5374 (0.111)	0.1027 (0.0399)	0.5669 (0.0352)	0.1319 (0.0813)	0.1774 (0.0119)
Luxembourg	1.63 (-)	196.0 (-)	0.4139 (-)	0.2499 (-)	1.0486 (-)	0.0111 (-)	0.1260 (-)
Netherlands	1.86 (0.14)	676.4 (623.7)	0.2309 (0.1225)	0.2160 (0.1635)	0.7544 (0.0772)	0.0302 (0.0204)	0.1273 (0.0188)
Norway	1.96 (0.11)	100.6 (313.8)	0.2606 (0.1476)	0.3139 (0.1672)	0.7797 (0.0233)	0.0165 (0.0101)	0.1430 (0.0189)
Poland	1.39 (0.13)	374.1 (704.9)	0.5260 (0.1927)	0.0543 (0.0213)	0.5471 (0.1044)	0.1551 (0.1063)	0.0746 (0.0238)
Portugal	1.26 (0.13)	170.6 (247.8)	0.2604 (0.15)	0.1728 (0.1376)	0.6789 (0.08)	0.1867 (0.1167)	0.1143 (0.0307)
Sweden	2.00 (0.08)	45.6 (66.4)	0.4112 (0.0958)	0.2364 (0.1714)	0.7112 (0.0466)	0.0338 (0.0171)	0.1708 (0.0176)
Slovakia	1.38 (0.17)	130.6 (68.5)	0.4809 (0.1157)	0.0558 (0.0379)	0.5679 (0.1667)	0.0358 (0.0142)	0.1645 (0.0336)
United Kingdom (England and Wales)	1.98 (0.15)	1449.9 (1824.6)	0.4306 (0.1304)	0.1642 (0.1223)	0.7384 (0.0359)	0.0135 (0.0176)	0.1469 (0.0209)
Source: National Statistical Offices, Eurostat, OECD, Author calculations							

Table B2. Reduced spatial lag modeling

	Model 6	Model 7	Model 8
Intercept	0.8274 *** (0.0502)	0.8287 *** (0.0502)	0.8935 *** (0.0534)
Population density	-0.0128 *** (0.0030)	-0.0153 *** (0.0031)	-0.0118 *** (0.0031)
GDP per capita		-0.0169 *** (0.0049)	-0.0141 ** (0.0049)
Share of divorced individuals			-0.5896 *** (0.1444)
ρ	0.4722 *** (0.0303)	0.4655 *** (0.0304)	0.4672 *** (0.0302)
AIC	-1710.6	-1720.5	-1735.2

Notes: N= 1,134; models controlled for country fixed effects; # p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.
Source: National Statistical Offices, Eurostat, OECD, Author calculations.


Legend
Country boundaries
NUTS 2 boundaries
2010 total fertility rate
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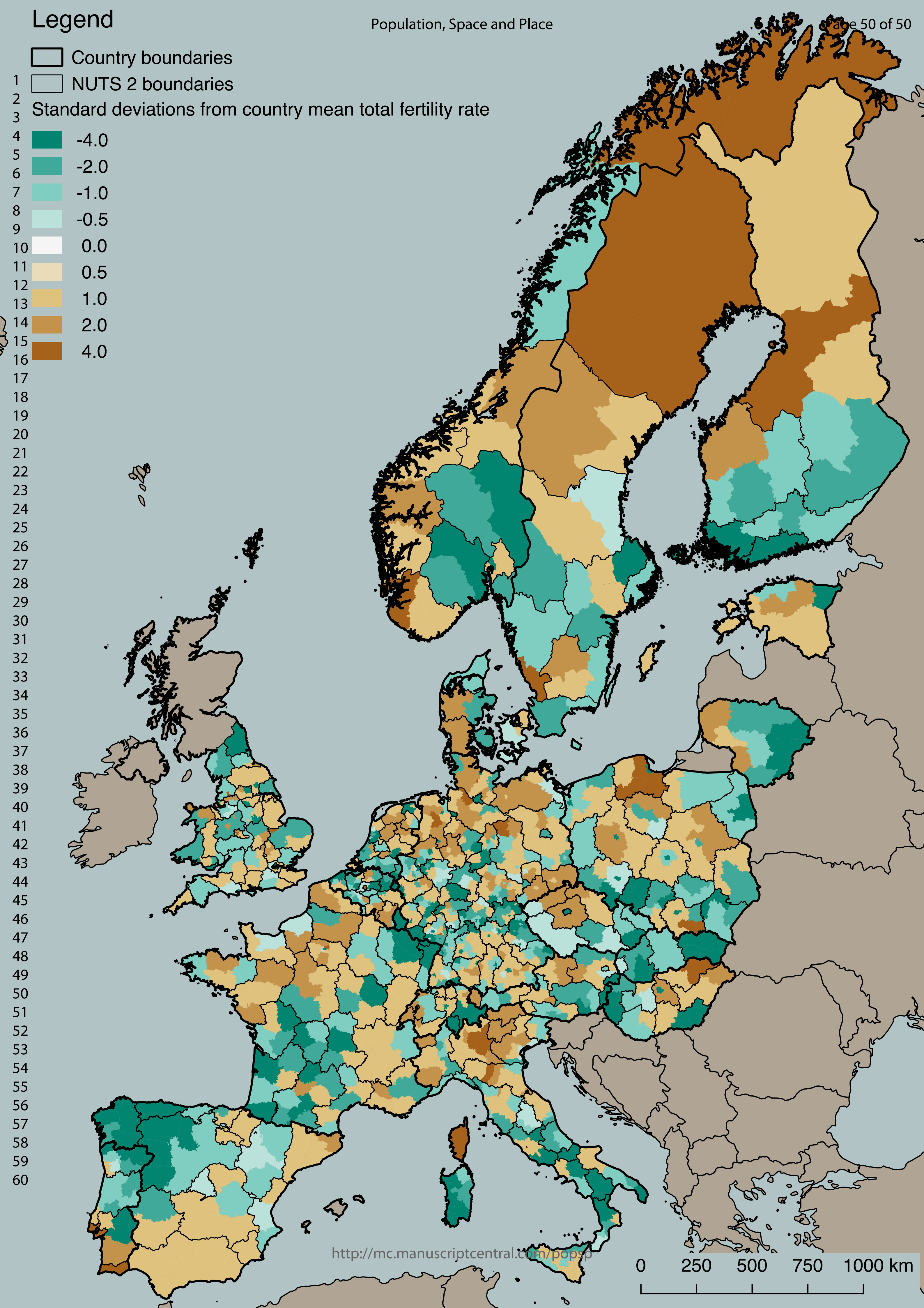
1.30 - 1.50
1.50 - 1.80
1.80 - 2.10
2.10 - 2.45
0
250
500
750
1000 km


Legend
Country boundaries
NUTS 2 boundaries
Standard deviations from country mean total fertility rate
-4.0
-2.0
-1.0
-0.5
0.0
0.5
1.0
2.0
4.0
0 250 500 750 1000 km