Spatial dependence multilevel model of well-being across regions in Europe

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Keywords: Well-being, Spatial dependence, Multilevel model

ABSTRACT
Understanding geographical perspective in explaining well-being is among the important issue in the subject. This study examines how nested and spatial structures explain variations in individual well-being across regions in Europe. We use the 2008 European Values Study, comprising 23,483 respondents residing in 200 regions (NUTS2) in Europe. Using spatial dependence multilevel model, the results show well-being to be spatially dependent through unobserved factors, meaning that well-being clusters because of clustering of unobserved factors. These findings suggest that addressing unobserved factors in neighbouring regions is an important issue for understanding individual well-being.

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Introduction

Well-being here refers to subjective evaluations on human optimal experience and functioning (Ryan & Deci, 2001). Current literature shows two aspects in understanding well-being: affective and cognitive aspects. The affective aspect or mood is represented by happiness, while the cognitive aspect is represented by life satisfaction (Lane, 2000). Although this paper focuses on well-being, we use the term well-being, life satisfaction and happiness interchangeably.

The relationships between well-being and its geographical dimensions have been examined by a number of studies (Aslam & Corrado, 2012; Ballas & Tranmer, 2012; Berreton, Clinch, & Ferreira, 2008; Okulicz-Kozaryn, 2011; Oswald & Wu, 2011; Stanca, 2010). These studies investigate cross-area distributions of well-being which conclude that there are different distributions of well-being across areas. Stanca (2010) suggests that geographical factors must be included in any explanation of well-being. More specifically, Oswald and Wu (2011) conclude that the state in which one lives makes a contribution to individual well-being.

It is important to study well-being from geographical perspective for two reasons. First, there is a spatial distribution of well-being among the geographic areas (Oswald & Wu, 2011). One area has specific level of well-being compared to other areas. Previous research suggests that different areas may create different levels of well-being (Pittau, Zelli, & Gelman, 2010). For example, people who live in rich regions tend to have higher level of well-being. In addition, Di Tella, MacCulloch, and Oswald (2003) suggest that well-being among Europeans is affected by macroeconomic factors (e.g. per capita GDP, unemployment rate). Second, most areas in the world have boundary with other areas or share borders with each other. These areas thus have their own spatial structure. For example, Stanca (2010) finds that there are spatial patterns among countries in explaining the effect economic indicators on well-being. In addition, Ertur, Galo, and Baumont (2006) and Niebuhr (2002) conclude that macroeconomic indicators among regions in Europe have spatial dependence structure.

Besides these important considerations, a major issue in conducting spatial research is to identify spatial scale. Aslam and Corrado (2012) argue that one of the most suitable groupings in Europe and to deal with data available in Europe is NUTS (Nomenclature of Territorial Units for Statistics) system of regional classification or regions. There are two main reasons for this. First, regions seem to have similar cultural and geographical characteristics that results in individual clustering across countries. In addition, Veenhoven (2009) argues that institutional variations across regions within nations tend to be similar. Therefore, identifying these smaller areas within nations may have better understanding of well-being. Second, Rampichini and D’Andrea (1997) suggest that regions should be considered as the macro-level since individuals living in a region have relatively similar socio-economic, political and cultural environment which contributes to well-being. Moreover, in Europe it is possible to observe stronger similarities (economic and socio-cultural) between certain areas of different countries than within the same country. Based on these
argument, we focus on NUTS level 2 as spatial scale and thereafter we use term region.

In attempting to examine how geographic factors affect well-being, the literature uses two methods of analysis: spatial dependence model and multilevel model. Spatial dependence model is used to estimate how the spatial structure of regions explains well-being. This model assumes that the characteristics of geographic areas may be dependent on each other as they share borders. For example, if regions A, B and C are neighbours, then this suggests that regions A, B and C may have similar levels of well-being, whereas the same cannot be said about non-neighbours regions X, Y and Z. Therefore, taking into account this spatial structure is likely to result in a better understanding of well-being. Studies that have already done so include Okulicz-Kozaryn (2011) and Stanca (2010), who suggest that well-being is indeed spatially structured.

Although these studies raise the understanding of how geographical factors explain well-being, they do so by using an area-aggregate of well-being data, ignoring multilevel structure of the data in which heterogenous individuals are nested within regions. It is essential to consider how this nested structure drives our understanding of individual well-being, for example how regional economic conditions impinge on individual residents’ well-being. To deal with this issue, multilevel model seems the most suitable. Only a few studies have so far used this. Pittau et al. (2010), for example, use multilevel model to examine economic disparity and individual life satisfaction across regions in Europe. More recently, Ballas and Tranmer (2012) use the same model to examine whether individual variations in happiness and well-being are attributable to individual, household, district or region characteristics.

Despite the usefulness of both spatial dependence and multilevel models in examining the geographical dimensions of well-being, these models are not without limitations. Spatial dependence model ignores multilevel structure of the data, while multilevel model ignores spatial dependence of neighbouring areas. To improve on this, we go further and follow Savitz and Raudenbush (2009) who propose an extension of these models by applying spatial dependence multilevel model. This model combines spatial contiguity at region level and nested structure of the data.

This paper aims to examine how the nested and spatial structures explain variations in individual well-being across regions in Europe. Using data from the 2008 European Values Study combined with regional statistics from Eurostat and digital boundaries from EuroBoundaryMaps, it is expected to advance our understanding how geographical dimensions explain well-being.

The results of this study suggest that well-being to be spatially dependent because of spatial dependence of unobserved factors. When using standard multilevel model, regional unemployment rate and per capita GDP have significant association with well-being. However, when spatial dependence multilevel is introduced, these contextual covariates become insignificant.

This paper is organised as follows: first, we identify the determinants of well-being in previous studies. We then describe the data and method used, including our construction of the covariates and the analytic strategy we used. In the penultimate section we present and discuss our results and their implications. Lastly, we conclude.

**Determinants of well-being**

Literature on the determinants of well-being is vast and still growing. Our review is thus by necessity selective (see Dolan, Peasgood, & White, 2008). Previous research however reveals a consistency among certain factors; these include health, companionship, unemployment and income.

Health is known to be an important determinant of happiness, the most often used measure of well-being. Reviewing some studies exploring various health-related indicators, including obesity, self-rated health and hypertension, Graham (2009) concludes that health has significant effect on happiness. More specifically, Gerdtam and Johannesson (2001) examine a national Swedish survey and conclude that certain socio-economic factors affect happiness through their impact on health.

Other than health, social interaction and companionship are also significant determinants in explaining well-being. Empirical studies within and across countries repeat the same result, indicating that family solidarity and friendship are strong predictors of well-being (Argyle, 2001). Moreover, Lane (2000) finds that in wealthy countries, companionship is even more important than income. The literature also shows that social capital, measured by participation in associations, has a positive correlation with well-being (Helliwell & Putnam, 2004).

On companionship, a number of studies discuss the impact of marital status on well-being: individuals derive social and emotional benefits from a supportive partner. Being married thus has a very high positive correlation with well-being, whereas being divorced and being widowed are detrimental to well-being (Argyle, 2001). There is also evidence that stable and secure intimate relationships are beneficial to happiness, and conversely that the dissolution of such relationships is damaging (Clark & Oswald, 2002; Graham, 2009).

Turning to one of the most important predictors of well-being, unemployment status has been recognised as a significant covariate of happiness. Previous studies (Clark & Oswald, 1994; Oswald, 1997) point out that unemployment is strongly and negatively associated with happiness, with severe and long-lasting negative impacts on well-being. These results cannot be interpreted only in terms of loss of income; there are significant non-pecuniary effects as well.

Another economic factor affecting well-being is income, the effect of which has become a major subject for debate in the literature. As far back as Easterlin (1974), research shows that personal income has a positive effect on happiness, but also that as GDP grows over time, happiness fails to follow. However, more recent studies examining this ‘Easterlin paradox’ have presented evidence to the contrary. Deaton (2008) demonstrates a positive relationship between per capita income and average happiness. Similarly, Inglehart, Foa, Peterson, and Welzel (2008) refer to the World Values Survey for 1981–2007 and find that as GDP per capita grows, well-being increases by as much as 77% in 52 countries across the world.

In terms of demographic factors, gender and age are the two standard covariates of well-being. Previous research concludes that women tend to be happier than men (Graham, 2009); one somewhat contentious explanation for this is that women tend to have a lower level of aspiration and thus a higher level of well-being (Frey & Stutzer, 2002). Age is also a significant covariate in the prediction of well-being; the association between the two is slightly positive (Argyle, 2001), with older people likely to be happier than younger ones. Previous studies have also found a U-shaped relationship between age and well-being (Blanchflower & Oswald, 2008; Clark, 2003): people tend to be happier when they are younger or older than when they are middle-aged.

Education may be one of the most intriguing determinants of well-being. A number of studies have investigated the relationship between the two (Diener, 2000; Diener, Sandvik, Seidtitz, & Diener, 1993; Stutzer & Frey, 2008), and suggest a positive correlation, due to the fact that education may lead to higher earning opportunities. In contrast, Clark and Oswald (1994) find a negative relation, which they conclude is due to education increasing aspirations and the
creation of an expectation among the more educated of a higher income. The resulting unmet expectation may drive the negative correlation between education and well-being.

Previous studies have identified a number of contextual covariates affecting well-being. These include regional GDP growth, regional unemployment rate, income inequality and traditional values. Graham (2009), for example, identifies a paradox in which GDP growth may give rise to social and economic problems (such as an increased crime rate) which are detrimental to happiness. Unemployment also has a negative effect on happiness (Frey & Stutzer, 2002), possibly due to fears that it will lead to a rise in the incidence of crime and social unrest. Di Tella, MacCulloch, and Oswald (2001), referring to data from 12 European countries over the period 1975—1991, also find that unemployment reduces life satisfaction. Alesina, Di Tella, and MacCulloch (2004) find that income inequality has detrimental effect on well-being. People who live in a country with high level of inequality are likely to have lower level of well-being compared to those who live in a more equal country.

In a cross-sectional settings such as Europe, we include traditional/secularism values as a measure of cultural variations. These provide a contrast between societies with high and low level in terms of: awareness of a religious life, the important of parent—child relationship, and the level of national pride that individuals have (Inglehart & Baker, 2000). Previous research has found that more traditional values are associated with lower levels of well-being (Li & Bond, 2010; Sagiv & Schwarz, 2000).

**Spatial dependence multilevel model of well-being**

Much of the research on well-being reviewed above is based on multiple regression, and despite their contribution to our understanding of well-being, they neglect the spatial and multilevel structure of the data. Few studies are the exception, exploiting the spatial or geographical dimension of well-being (Okulicz-Kozaryn, 2011; Oswald & Wu, 2011; Stanca, 2010); some explore multilevel structure of happiness data (Aslam & Corrado, 2012; Ballas & Tranmer, 2012; Pittau et al., 2010; Rampichini & D’Andrea, 1997).

Oswald and Wu (2011) use the Behavioral Risk Factor Surveillance System to examine the geographical dimension of life satisfaction and mental health in the United States. Using the individual as the unit of analysis, they find that the state of Louisiana and the district of Columbia exhibit high levels of psychological well-being, while those levels in the states of California and West Virginia are low. Although this study sheds some light on the geographical dimension of well-being, it is limited by its use of an aggregate level of happiness and linear regression. It does not explore multilevel structure (i.e. that individuals reside in states) and the spatial structure (i.e. that the state of Massachusetts shares a border with New Hampshire and Connecticut) of the data.

To better understand spatial mechanism, we refer to the so-called first law of geography: ‘Everything is related to everything else, but near things are more related than distant things’ (Tobler, 1970). To test this law, spatial econometrics is a suitable approach (Anselin, 1988), as it addresses the spatial dependence structure. Anselin (1988) states that ‘spatial dependence can be understood as the lack of independence among observations’.

Spatial dependence can be elaborated in two mechanisms: as a diffusion and a spatial externalities (Morenoff, 2003). Diffusion illustrates a spatial process intrinsic to a given outcome, while spatial externalities describe spatial processes generated by explanatory variables which spread into neighbouring geographic areas. From diffusion mechanism, well-being may be viewed as spatially dependent among region in Europe because well-being in one region is contagious with that in neighbouring regions. Meanwhile, spatial externalities mechanism views that well-being may be spatially dependent because the covariates or error terms affecting well-being are spatially dependent.

Among the first to apply spatial dependence approach to the study of well-being, Stanca (2010) examines the spatial structure of the effect of a country’s economic conditions on subjective well-being. Using aggregate happiness data taken from the World Values Survey, the study uses a two-step methodology. First, it estimates the effect of economic conditions on the life satisfaction of individuals. Second, it examines the relationship between the effects of individual economic conditions on subjective well-being and macroeconomic conditions. These effects are used as dependent variables in cross-country regressions, while the macroeconomic conditions are used as independent variables. The study finds that before controlling for country covariates, the effect of individual income on subjective well-being is spatially dependent, but that after controlling for covariates, the estimate for spatial dependence becomes insignificant. Stanca’s thus contributes to the understanding of how spatial structure may explain the effect of income on subjective well-being. Conversely, ignoring this structure may result in bias in estimating well-being.

Okulicz-Kozaryn (2011) uses Eurobarometer data from 1996 to explore the geography of life satisfaction across regions (NUTS 2) in Europe, exploiting geographical areas in more detail. Using Local Indicators of Spatial Association (LISA) proposed by Anselin (1995), this study concludes that life satisfaction is spatially positively correlated - that is, regions are surrounded by other regions with relatively similar levels of life satisfaction. Although this study provides important understanding into how spatial structure explains life satisfaction, it uses aggregated levels of life satisfaction without including any covariates.

A further limitation of these spatial econometrics studies of well-being is that they focus on spatial dependence, while neglecting nested structure in which individuals live in certain areas (such as household, neighbourhood, district, region and country). To deal with this structure, multilevel model is most suitable. Pittau et al. (2010) use the 1992—2002 Eurobarometer surveys to carry out multilevel analysis to examine the effect of economic disparity on life satisfaction in European regions. They conclude that the regional dimension is relevant to any estimation of life satisfaction, even after controlling for individual characteristics and the differing effects of income.

Aslam and Corrado (2012) apply multilevel model and use the Wave 4 of the European Social Survey to examine regional variations to explain well-being. Their study not only uses the random effect but also the country fixed effect. Their findings are those who live in Denmark, Spain, Sweden and Ireland have higher level of well-being than those who live in the rest of EU countries. The study concludes that not only individual but also regional economic and non-economic factors (such as social capital) have a significant effect on well-being.

More recently, Ballas and Tranmer (2012) examine multilevel structure and the geographical dimension of happiness and well-being. Using combined data from the 1991 Census Samples of Anonymised Records (SARs) and the 1991 British Household Panel Survey, they provide an important insight into how best to approach the study of happiness. However, they leave some questions unanswered; they do not, for example, explain the spatial dynamics of well-being, such as the spatial dependence of the outcome.

To sum up, the two methods used for analysing well-being: spatial dependence model and multilevel are no without criticism. Given the spatial contiguity of regions, the independence assumption regarding the neighbourhood random effects is implausible and in turn regions may be dependent each other (Savitz & Raudenbush, 2009). If errors at region level are correlated,
the assumption of multilevel model is violated. Meanwhile, spatial dependence model does not take into account nested structure of data. To overcome the limitation of these two models, spatial dependence multilevel model seems suitable.

We thus aim to answer three research questions. First, is well-being spatially dependent across regions in Europe? Second, what is the mechanism through that explains the process? Third, does spatial dependence multilevel improve estimates and inference of well-being?

Data and methods

To examine how the spatial and nested structure explain well-being across regions in Europe, we use data from the 2008 European Values Study (EVS). This covers 47 countries, 200 regions and 23,483 individual respondents, and its purpose is to enhance understanding of the ideas, beliefs, preferences, attitudes, values and opinions of citizens across Europe. It also contains information on happiness and region code (NUTS2). This region code allows us to match the data with those from the Eurostat regional database to examine the effect of contextual factors on happiness. More importantly, the data is also matched with digital boundary data from EuroBoundaryMaps 5.0, allowing us to examine the spatial dependence structure of regions in Europe.

Dependent variable

In this paper we use well-being as the dependent variable, measured by happiness question ‘Taking all things together, would you say you are ‘very happy’, ‘quite happy’, ‘not very happy’ or ‘not at all happy’? In terms of the scale of the variable, some studies (Praag & Ferrer-i-Carbonell, 2007) treat well-being as an ordinal scale, thus needs to be estimated by ordinal logistic multilevel regression. However, Frey and Stutzer (2002) suggest that ordinality or cardinality scale of subjective well-being does not make big difference in results. Thus, the use of linear model is expected to be similar as the use of ordinal scale in findings. Since the software used in estimating the model at the moment only provides linear model, we treat well-being as continuous.

Individual covariates

Individual covariates used in this study include health, association membership, gender, age, education, marital status, employment status and household income. Health is measured by individual self-rating on a five-point ordinal scale, ranging from ‘very poor’ (1) to ‘very good’ (5). To measure association membership, we ask: ‘Please look carefully at the following list of voluntary organisations and activities and say: a) Which, if any, do you belong to? and b) Which, if any, are you currently doing unpaid voluntary work for?’ Possible answers consist of 15 voluntary organisations, and to calculate membership, we use the total of number voluntary associations followed by a respondent.

We create a dummy variable to measure gender (1 for female, 0 for male). Education is measured by the highest level of education attained by respondents, ranging from pre-primary to the second stage of tertiary education. Marital status is measured using dummy variables for ‘in union’, ‘widowed’, and ‘divorced’, with ‘never married’ as the reference group. Another measure of socio-economic covariates is employment status, differentiated as ‘retired’, ‘home-maker’, ‘student’, ‘unemployed’, and ‘disabled’. These are used as dummy variables with ‘employed/self-employed’ as the reference group. Lastly, income is calculated by the log of median household income.

Contextual covariates

To measure regional economic conditions, we use regional per capita GDP, GDP growth and the unemployment rate, obtained from Eurostat regional data (Eurostat 2010). Di Tella et al. (2001), referring to data from 12 European countries over the period 1975–1991, also find that unemployment reduces life satisfaction. Alesina et al. (2004) find that income inequality has detrimental effect on well-being.

Moving to country level covariates, we include income inequality, traditional/secularism values and welfare state regimes. People who live in a country with high level of inequality are likely to have lower level of well-being compared to those who live in a more equal country. We use the Gini index at country level obtained from UNU-WIDER to measure income inequality. Since well-being may be affected by economic systems established in a country where individuals live, we follow Esping-Andersen (1990) to differentiate welfare state regimes and create dummy variables for living in continent, liberal and rest of Europe countries, while social democratic countries as a reference.

Analytic strategy

The aim of this study is to examine how nested and spatial structures of the data explains well-being across regions in Europe. We first examine the nested structure of data using multilevel model, by then including spatial structure among the group or level-2 data. To estimate this data, spatial dependence multilevel model is used as the most suitable method. Since it is a combination of multilevel model and spatial dependence model, we begin to briefly describe both methods.

Multilevel model is used to account for the nested structure of data. Specifically, it can be used to address spatial heterogeneity, assuming that the association between the dependent variable and its covariates can vary between levels (Ballas & Tranmer, 2012). However, this model only captures nested structure where individuals reside in regions. This nested structure gives the model below:

\[ Y_{ij} = X_{ij} \beta_j + \mu_j + \epsilon_{ij} \]  

(1)

\[ \epsilon_{ij} \sim N(0, \sigma^2_e) \]  

(2)

\[ \mu_j \sim N(0, \sigma^2_\mu) \]  

(3)

\[ \mu \perp \epsilon \]  

(4)

Note that each regions’ error term, \( \mu_j \), are independently distributed. To express this more visually, we choose maps of regions in Germany to show how standard multilevel model treats the level-2 structure of the data. In Fig. 1 each region has one \( \mu \), unconnected with other \( \mu \) (compare with Fig. 2). Since level 2 is assumed to be independently distributed, this model cannot address spatial dependence among level 2 units.

To improve on this, we consider spatial dependence model. Spatial dependence can be examined through spatial lag and spatial error model (Anselin, 1988; Ward & Gleditsch, 2008). Using spatial lag, we can interpret that spatial dependence occurs directly through dependent variable. Meanwhile using spatial error model, we can interpret that spatial dependence comes only through error terms. Ward and Gleditsch (2008) argue that these models may seem superficially similar, as each model suggests spatial dependence between observations. Elaborated by Anselin (1988), these
models capture spatial dependence among geographical areas or neighbouring areas. The reduced specification is below.

\[ y_i = X\beta + \rho Wy + \epsilon \]  
\[ y_i = X\beta + \epsilon \]  
\[ \epsilon = \rho W\epsilon + \eta \]

Equation (5) represents spatial lag model, while equations (6) and (7) represent spatial error model, where \( y \): dependent variable, \( \epsilon \): error term, \( \rho \): degree of spatial dependence, \( W \): spatial contiguity weight matrix. Savitz and Raudenbush (2009) combine these two models by correcting error terms in standard multilevel model using spatial error model (see Anselin, 2003). By doing this, the underestimation of standard error may be avoided. They propose a spatial dependence multilevel model, where the spatial structure of level 2 units (e.g. regions) is taken into account. At the same time, nested structure of the data is also addressed. In spatial dependence multilevel model we have:

\[ y_{ij} = X_{ij}\beta_{ij} + \mu_j + \epsilon_{ij} \]  
\[ \mu_j = \rho W\mu_j + \eta_j \]  
\[ y_{ij} = X_{ij}\beta_{ij} + \rho W\mu_j + \eta_j + \epsilon_{ij} \]  
\[ \epsilon_{ij} \sim N\left(0, \sigma^2_\epsilon\right) \]  
\[ \eta_j \sim N\left(0, \sigma^2_\eta\right) \]  
\[ \eta \perp \epsilon \]

where \( \rho \): degree of spatial dependence, \( W \): spatial contiguity weight matrix. Note that each region’s error term, \( \mu_j \), is now spatially correlated. As opposed to the linear multilevel model, the new parameters to be estimated are \( \rho \) and \( \eta \). Equation (10) shows the full equation of spatial dependence multilevel model.

The result of \( \rho \), which is included in error term (\( \mu_j \)), shows the degree to which spatial dependence of outcome through error term is introduced. In other words, spatial dependence of well-being is due to spatial dependence of unobserved factors. Savitz and Raudenbush (2009, p. 160) interpret that ‘when \( \rho \neq 0 \), the spatial dependence of the sites is introduced. For example, \( \rho > 0 \) indicates that a site typically surrounded by other sites with similar values on the outcome. On the other hand, \( \rho < 0 \) indicates that high-value sites are typically surrounded by low-value sites, and vice versa. Finally, \( \rho = 0 \) indicates no spatial dependence’.1

Using Germany as an example, Fig. 2 shows the level 2 structure of spatial dependence multilevel model in which regions are spatially dependent. Clearly, this model can capture both spatial dependence and multilevel which we have identified as essential to estimate well-being.

### Results

We begin with the descriptive statistics and the map of happiness in regions across Europe, then present the results from multilevel model and spatial dependence multilevel model. Table 1 reports descriptive statistics for all variables. The latest version of the European Values Study 2008 consists of 67,786 respondents, but we restrict the sample to respondents aged 15–70, with average of 43.9 years old. Due to data from both individual and contextual covariates being missing, the full data consists of 23,483 respondents in 200 regions. Of the respondents, 55% are female, 56% are married, 55% live in rest of Europe.

Map 1 shows the mean of happiness across regions in Europe, and demonstrates that happiness varies within each country. In Sweden for example, happiness levels in the south tend to be higher than those in the north. Regional differences can also be seen in the UK, with parts of Scotland, Cumbria and Essex being among the most happy regions of Europe. Meanwhile, inhabitants

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1 The same interpretation is also used in previous studies (Baller, Anselin, Messner, Deane, & Hawkins, 2001; Beck, Gleditsch, & Beardsley, 2006; Brueckner, 2002). Spatial dependence of outcome is due to spatial dependence of error terms. For example, Baller et al. (2001, p. 583) wrote ‘In the non-South, in contrast, the spatial patterning of homicide rates is more consistent with a spatial error model (at least in the last three decades). This implies that homicide rates cluster because of the clustering of unmeasured variables’.
of the regions of Bolzano in Italy, Rheinhessen-Pfalz in Germany, Autonoma de Ceuta in Spain, and the Algarve in Portugal are among the least happy regions of Europe.

Our task is to examine how nested and spatial structure among regions in Europe explain well-being. Table 2 presents results from two kinds of multilevel models: standard multilevel model and spatial dependence multilevel model. Model 1 represents a null model of standard multilevel model, while model 2 shows a null model of spatial dependence multilevel model. From both models we find a quite similar value of intraregion correlation (11.2% and 10.6%), which indicates that the variations in individual well-being at regional level is non-negligible. When we include the spatial dependence structure (model 2), we find that $\rho = 0.834$, meaning that 83.4% of causes of well-being come from unobserved factors in neighbouring regions. More specifically, unobserved factors of well-being in one regions have positive correlation with unobserved factors of well-being in surrounding regions.

Comparing the constant coefficients and standard errors from standard multilevel and spatial dependence multilevel model, we find that the intercept of multilevel spatial dependence model is smaller than that of standard multilevel model. Moreover, we also find that the standard errors of the two models are different (0.035 compared to 0.017), indicating an underestimation of the standard errors when spatial dependence is ignored. To determine the best fit model, we find DIC difference $= 149.82$ ($p < 0.001$), in which model 2 has lower level of DIC. This indicates that model 2 is better than model 1, thus concluding that addressing spatial dependence in the model yields better estimates of well-being.

The remainder of Table 2 explores the individual and contextual factors affecting well-being, since well-being is also influenced by regional factors. Model 3 presents the result of standard multilevel model and adds individual and regional covariates of well-being. Consistent with earlier studies findings, being healthy, being a member of an association, being trustful and being in a marriage are positively associated with well-being. Meanwhile, being unemployed, being widowed, and being separated are negatively associated with well-being. In terms of contextual covariates, unemployment rate has a negative effect on well-being, while living in regions with high level GDP tends to have high level well-being.

Model 4 illustrates spatial dependence multilevel model and adds individual and regional covariates. The results suggest that well-being is spatially-dependent through unobserved factors with $\rho = 0.790$, even after controlling for standard individual and contextual covariates. The value of $\rho = 0.790$ means that 79% of causes of well-being come from unobserved factors present in neighbouring regions. Most coefficients in this model are relatively
similar to the those of model 3. However, the unemployment rate and regional GDP coefficient become smaller and insignificant which indicate that spatial dependence among regions in Europe matters.

Model 5 shows how country level covariates affect well-being. Living in inequal countries and living in high level traditional countries and living at continent countries and living at the rest of Europe over, looking at welfare regime states, the results indicate that spatial dependence among regions in Europe. One of its major finding is that well-being is positively and significantly associated with well-being. A similar result can be seen when comparing those who are separated and who have never married with those in a union, with both having a significant negative effect on well-being. Being unemployed and being a homemaker tends to make one less happy than being employed or self-employed.

**Discussion**

This study presents spatial dependence multilevel model and its usefulness in explaining variations in individual well-being across regions in Europe. One of its major finding is that well-being is spatially dependent through unobserved factors, even after controlling for standard individual, regions and countries covariates of well-being. This spatial dependence occurs because unobserved factors of well-being in surrounding regions. Since spatial dependence multilevel model improves multilevel model through spatial error model, the results may only be explained by spatial externalities, not diffusion. This means that well-being cannot spread directly through the contiguity among regions, but it can be explained by unobserved factors in neighbouring regions. Although we have included these contextual covariates of well-being, there are unobserved factors which spread from one to neighbouring regions.

The present study also finds that regional factors do indeed have an effect on well-being, with some of the variation in the measures of well-being being attributable to region level variations. We find the association between a region’s contextual factors and its well-being to be non-negligible, a result which supports Aslam and Corrado (2012), who conclude that regional economic factors

### Table 2

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<td>0.031(0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>-0.020(0.002)</td>
<td>-0.020(0.002)</td>
<td>-0.020(0.002)</td>
<td>-0.020(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td>0.004(0.004)</td>
<td>0.005(0.004)</td>
<td>0.005(0.004)</td>
<td>0.006(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Union</strong></td>
<td>0.182(0.012)</td>
<td>0.184(0.011)</td>
<td>0.184(0.012)</td>
<td>0.184(0.011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Widow</strong></td>
<td>-0.081(0.022)</td>
<td>-0.081(0.019)</td>
<td>-0.080(0.022)</td>
<td>-0.081(0.019)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Separated</strong></td>
<td>-0.033(0.016)</td>
<td>-0.035(0.015)</td>
<td>-0.037(0.016)</td>
<td>-0.034(0.015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Professional</strong></td>
<td>0.014(0.009)</td>
<td>0.013(0.010)</td>
<td>0.014(0.009)</td>
<td>0.012(0.010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Intermediate</strong></td>
<td>0.032(0.011)</td>
<td>0.031(0.014)</td>
<td>0.032(0.012)</td>
<td>0.031(0.014)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Pensioner</strong></td>
<td>0.021(0.012)</td>
<td>0.019(0.012)</td>
<td>0.019(0.012)</td>
<td>0.018(0.012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Housekeeper</strong></td>
<td>0.025(0.018)</td>
<td>0.022(0.016)</td>
<td>0.023(0.019)</td>
<td>0.020(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Student</strong></td>
<td>0.017(0.020)</td>
<td>0.019(0.019)</td>
<td>0.018(0.020)</td>
<td>0.018(0.019)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Unemployed</strong></td>
<td>-0.149(0.021)</td>
<td>-0.151(0.016)</td>
<td>-0.154(0.021)</td>
<td>-0.154(0.017)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Disabled</strong></td>
<td>-0.046(0.030)</td>
<td>0.040(0.028)</td>
<td>0.044(0.030)</td>
<td>0.039(0.028)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Log household income</strong></td>
<td>0.063(0.007)</td>
<td>0.059(0.006)</td>
<td>0.058(0.007)</td>
<td>0.057(0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Contextual</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Regional GDP growth</strong></td>
<td>-0.004(0.004)</td>
<td>-0.001(0.003)</td>
<td>-0.007(0.003)</td>
<td>-0.002(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Regional GDP</strong></td>
<td>0.034(0.012)</td>
<td>-0.004(0.011)</td>
<td>0.010(0.012)</td>
<td>-0.005(0.010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Regional unemployment rate</strong></td>
<td>-0.008(0.003)</td>
<td>-0.003(0.003)</td>
<td>-0.002(0.003)</td>
<td>0.001(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Emmision</strong></td>
<td>-0.010(0.017)</td>
<td>-0.004(0.013)</td>
<td>-0.005(0.015)</td>
<td>-0.011(0.012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Country Gini index</strong></td>
<td></td>
<td></td>
<td>-0.020(0.003)</td>
<td>-0.017(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Traditional value</strong></td>
<td></td>
<td></td>
<td>-0.144(0.020)</td>
<td>-0.148(0.023)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Continent</strong></td>
<td></td>
<td></td>
<td>-0.125(0.042)</td>
<td>-0.181(0.052)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Liberal</strong></td>
<td></td>
<td></td>
<td>0.009(0.045)</td>
<td>-0.061(0.068)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Rest</strong></td>
<td>-0.115(0.053)</td>
<td>-0.113(0.053)</td>
<td>-0.138(0.064)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Variances at level 1</strong></td>
<td>0.395</td>
<td>0.395</td>
<td>0.319</td>
<td>0.320</td>
<td>0.319</td>
<td>0.319</td>
</tr>
<tr>
<td><strong>Variances at level 2</strong></td>
<td>0.050</td>
<td>0.047</td>
<td>0.019</td>
<td>0.021</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td><strong>ICC</strong></td>
<td>11.2%</td>
<td>10.6%</td>
<td>5.6%</td>
<td>6.1%</td>
<td>3.6%</td>
<td>3.6%</td>
</tr>
<tr>
<td><strong>DIC</strong></td>
<td>45,343.91</td>
<td>45,194.09</td>
<td>40,044.95</td>
<td>39,971.02</td>
<td>39,968.36</td>
<td>39,916.35</td>
</tr>
</tbody>
</table>

Significance: †: 5%; ‡: 1%.
matter for individual well-being. However, the use of multilevel model without incorporating spatial dependence structure among region can result in bias estimates.

The finding on the unemployment rate supports earlier research (Di Tella et al., 2003) and indicates that both the unemployed and the employed suffer when this rate goes up. The unemployed have less chance of getting a job; those in employment fear the possibility of losing theirs. Both groups may be impacted by attendant negative effects of a high or growing unemployment rate, such as increased crime, social tension and violent protest (Frey, 2008). However, when spatial dependence multilevel model is introduced, the unemployment rate becomes insignificant in explaining well-being. This may be caused that unobserved factors at neighbouring regions are more associated with well-being and in turn decrease unemployment rate coefficient.

Living in countries with high level of inequality, and in countries which score highly on traditional values, all have a negative effect on well-being. These results support the findings of previous studies (Alesina et al., 2004; Hayo & Seifert, 2003; Li & Bond, 2010). The result indicates that traditional values have a negative effect on well-being which supports previous research (Sagiv & Schwarz, 2000). This may be because in individualistic culture like in Europe, many people place high value on individual freedom. Those who live in a traditional culture (which contradicts individualistic values) have a lower level of well-being.

Results from individual covariates reveal that strong covariates of well-being include health, marital status and individual unemployment. Healthy people tend to be happy people, a result which supports previous studies (Argyle, 2001; Frey, 2008; Graham, 2009). The reason for this high correlation is that the variables of health and well-being are subjective measures which supplement each other. Well-being measure may involve subjective health assessment and vice versa.

Being married (or in a committed partnership) is an important factor for predicting well-being, providing, among others, companionship. As has been argued by Argyle (2001) and Lane (2000), social relations (including marriage and friendships) are the factors with the most significant impact on well-being. Argyle (2001) also states that marriage can enhance self-esteem by providing an escape from stress in other parts of one’s life. In addition, married people benefit from an intimate relationship and suffer less from loneliness.

Turning to individual unemployment, this research supports previous results (Clark & Oswald, 1994; Di Tella et al., 2003), namely that unemployed people appear to have a lower level of well-being than those in employment. Unemployment almost always leads to loss of income, often with an attendant increase in depression and anxiety. Understandably therefore, being unemployed exhibits lower levels of well-being compared to any other single characteristic (including significant negative ones such as being divorce and being separated).

Our research has several limitations. Further studies are needed to include unobserved factors to the specification for examining whether spatial dependence of well-being through unobserved factors remains high. In addition, we have missing data problem especially on income and contextual covariates; regional per capita GDP and unemployment rates. The analytical depth of future research would be improved by referring to recent developments of multiple imputation especially in a multilevel structure (Carpenter & Kenward, 2013).

Conclusion

In this paper, we have provided new insight how contextual and geographical dimensions explain well-being. Well-being across region in Europe is not randomly distributed, but spatially dependent: regions with a higher level of well-being are surrounded by a higher level of well-being through unobserved factors at neighbouring regions. Moreover, spatial dependence of well-being persists even after controlling individual and contextual covariates. Other than that, we conclude that the variations of well-being is attributable to the regional level. We have also shown that spatial dependence multilevel model is suitable for understanding well-being across regions in Europe. This study proves an evidence that ignoring multilevel and spatial structure at the same time would be misleading. Future studies on well-being or health related outcomes which exploit the nested and spatial structures may use spatial dependence multilevel model in improving estimates of outcomes.

One major implication for public policy is that treating regions as isolated islands may be misguided, and that European governments, by addressing not only development within a region, may also bring benefits to surrounding regions. Finally, the fact that well-being is spatially dependent through unobserved factors across regions suggests that it needs to be addressed not only within countries but also across countries, especially around the borders.

Acknowledgments

We would like thank to Directorate of Higher Education, Ministry of Education and Culture, Indonesia for providing funding of this study and the original creators of European Values Study for providing the survey available. We would also like thank to Sujawoto, Devi Femina, Paul Widdop, Citra Jaya, Asri Maharani and Wulung Hanandita and the anonymous reviewers for their help in improving this manuscript.

References

References


