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Are Regional Differences in Personality and their Correlates robust? Applying Spatial Analysis Techniques to Examine Regional Variation in Personality across the U.S. and Germany

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Abstract:

There is growing evidence that personality traits are spatially clustered across geographic regions and that regionally aggregated personality scores are related to political, economic, social, and health outcomes. However, much of the evidence comes from research that has relied on methods that are ill-suited for working with spatial data. Consequently, the validity and generalizability of that work is unclear. The present work addresses two main challenges of working with spatial data (i.e., Modifiable Aerial Unit Problem and spatial dependencies) and evaluates data-analytic techniques designed to tackle those challenges. Using analytic techniques designed for spatial data, we offer a practical guideline for working with spatial data in psychological research. Specifically, we investigate the robustness of regional personality differences and their correlates within the U.S. (Study 1: N = 3,387,303) and Germany (Study 2: N = 110,029). To account for the Modifiable Aerial Unit Problem, we apply a mapping approach that visualizes distributional patterns without aggregating to a higher level and examine the correlates of regional personality scores across multiple levels of spatial aggregation. To account for spatial dependencies, we examine the correlates of regional personality scores using spatial econometric models. Overall, our results suggest that regional personality differences are robust and can be reliably studied across countries and spatial levels. At the same time, the results also show that ignoring the methodological challenges of spatial data can have serious consequences for research concerned with regional personality differences.

Keywords: Geographical Psychology, Personality, Spatial Analysis

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Introduction

Geographical psychology seeks to identify and understand the spatial distributions of psychological phenomena and their relations to features of the macro environment (Rentfrow & Jokela, 2016). Research in this area tends to focus on questions concerning the spatial organization of personality traits, the mechanisms responsible for their organization, and how that organization relates to micro and macro-level outcomes. In recent years, a significant number of investigations have examined such questions. As can be seen in Figure 1, the total stock of personality articles published between 2001 and 2019 grew by 82% (from 109,654 to 200,446), while the stock of personality articles containing the stemmed expression "*geogr**" in their abstract or list of subjects grew by 151% (from 214 to 537). Moreover, among those 537 studies that examined geographical content, studies looking at regional differences expanded particularly rapidly: Before 2000, only 33 personality articles containing *geogr** and *region** had been published. But between 2001 and 2019, that number grew by 300% to 132 articles with a particular steep increase in the last ten years. These trends clearly demonstrate a growing and significant interest in the geographical distribution of psychological phenomena.

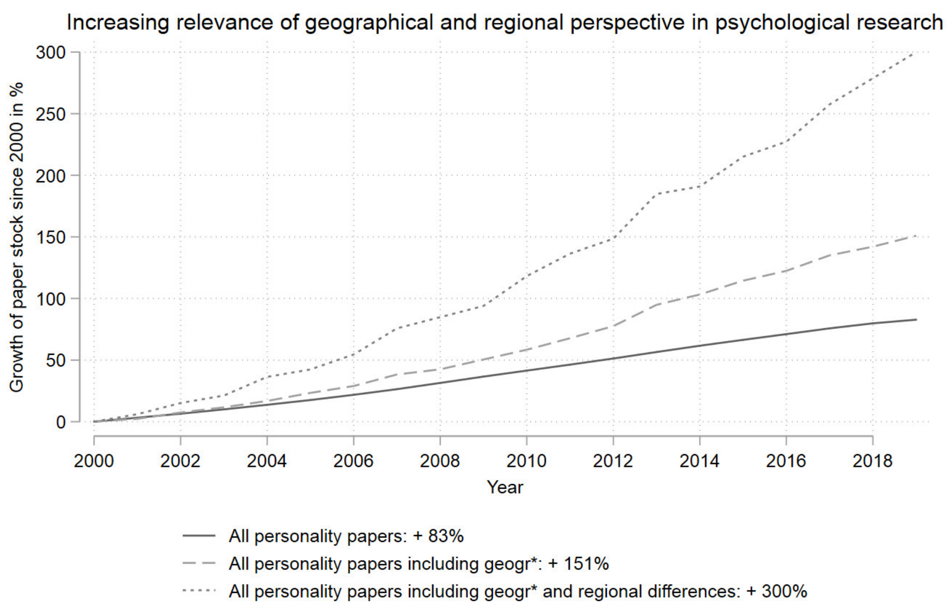

Figure 1. Growth of article that listed geographical and regional keywords since 2000.

[1]The psychological investigations concerned with geography have focused on a broad range of phenomena, from culture, ideology, and economics, to personality, values, health, and well-being. Studies have shown that such geographical differences in psychological phenomena can shed new light on fundamentally important questions. For example, regional differences in personality have advanced our understanding why some places are economically more successful than others (Obschonka, Schmitt-Rodermund, Silbereisen, Gosling, & Potter, 2013; Obschonka et al., 2015), why places vote conservative or liberal governments into power (Obschonka, Stuetzer, Rentfrow, Lee, Potter, & Gosling, 2018; Rentfrow, Jost, Gosling, & Potter, 2009), or why people in some places live longer lives than in others (McCann, 2010b, Voracek, 2009).

The findings from that work have important implications for understanding (1) how historical and institutional factors contribute to psychological development and expression, and (2) how the psychological characteristics of individuals contribute to the political, economic, and social landscape of regions[2]. In this way, geographical psychology has the potential to bridge psychological theory and research with the social and behavioral sciences. Crucially, the empirical foundation on which to establish such conceptual bridges requires robust research methods. However, the majority of studies in geographical psychology have relied on statistical techniques that are well-suited for analyzing psychological data, but not spatial data, which raises questions about the veridicality of the findings.

Fortunately, there are analytical techniques designed specifically to handle spatial data that can be used to analyze geographical differences in psychological constructs.

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[1] We searched via EBSCOhost in the databases PsycARTICLES and PsycINFO and only included peer-reviewed publications. To identify studies concerned with geographical subjects we searched abstracts and subjects using the Boolean search phrases *"personalit*" NOT "personality disorder".* For identifying geographical studies we added the phrase AND "*geogr**" and for geographical studies interested in regional differences we added the phrase AND *"region*"*.

[2] The terms r*egion* and *regional* here follow the classic definition of a spatial-geographical entity of medium scale, which is settled between the neighborhood and the national level (WIECHMANN, 2000).

Combining psychological research methods with spatial analytic methods will enable researchers to (1) scrutinize the validity of previous results against the backdrop of perennial alternative explanations, (2) develop a more nuanced understanding of geographical psychology and its far-reaching effects, and (3) take a decisive step towards connecting psychological and geographical science. The present paper makes a first attempt at overcoming the limitations of previous research by applying rigorous spatial analytic techniques to examine regional personality differences and their correlates across regions of the U.S. and Germany.

Evidence for Geographical Differences in Psychology

Most of the early research concerned with geographical differences has focused on cross-country differences in personality and well-being. For example, McCrae and colleagues published a number of articles on national differences in the Big Five personality domains (i.e., extraversion, agreeableness, conscientiousness, neuroticism, openness; e.g., Allik & McCrae, 2004; McCrae, 2001; McCrae & Terracciano, 2008; McCrae, Terracciano et al., 2005a, 2005b), and Diener and colleagues published several papers on national differences in well-being (e.g., Diener, Helliwell, & Kahneman, 2010; Diener, Oishi, & Lucas, 2015). Such comparisons are important because they inform our understanding of how people in various parts of the world differ on particular psychological characteristics, and they also shed light on the political, economic, social, historical, and cultural factors that may contribute to those differences.

More recent studies in geographical psychology have begun to focus on regional differences within countries. Research concerned with such differences has focused on a range of constructs, including well-being (Obschonka et al., 2018), collectivism (Conway et al., 2001), religiosity (Gebauer et al., 2017), character strengths (Park, Peterson, & Seligman, 2006), moral judgment (Graham, Meindl, Beall, Johnson, & Zhang, 2016), agency

(Kitayama, Ishii, Imada, Takemura, & Ramaswamy, 2006), self-control (Findley & Brown, 2017), empathy (Bach, Defever, Chopik, & Konrath, 2017), tightness-looseness (Harrington, & Gelfand, 2014), political ideology (Motyl, Iyer, Oishi, Trawalter, & Nosek, 2014), attachment orientation (Chopik & Motyl, 2017), racial bias (Hehman, Flake, & Calanchini, 2018), and courage (Ebert, Götz, Obschonka, Zmigrod, & Rentfrow, 2019).

Considerably attention has been given to regional differences in the Big Five (Rentfrow & Jokela, 2016). For example, Rentfrow et al. (2008) examined regional differences in the Big Five across states in the U.S. The results from that research and more recent investigations indicate that the Big Five are regionally clustered within the U.S. (Elleman, Condon, & Revelle, 2018; Obschonka, Lee, Rodriguez-Pose, Eichstaedt, & Ebert, 2019; Rentfrow et al., 2013). For example, average levels of openness are high in the Northeast and West coast, while average levels of openness are low in the Midwest and South-Central regions. Most studies of regional differences in the Big Five have focused on the U.S., but a few studies have examined variation in other countries. For example, Allik et al. (2009) examined personality variation from 39 different samples across 33 selected federal states in Russia and found subtle regional differences in mean personality scores. Rentfrow et al. (2015) examined personality differences across Great Britain and observed distinct regional clusters for agreeableness and openness. Obschonka et al. (2019) explored personality differences across East and West, as well as North and South Germany. Götz, Ebert, and Rentfrow (2018) revealed personality differences across 26 cantons in Switzerland, and Wei et al. (2017) found personality differences within China. Taken together, the results from existing studies strongly suggest that there are regional personality differences in many nations around the world.

Most studies of geographical differences in the Big Five have focused on large geographical areas, such as countries and states, but a few investigations have examined geographical variation in smaller spatial units, such as counties, cities, and neighborhoods. For example, Obschonka et al. (2019) revealed pronounced regional personality differences (estimated from Twitter language) across 1,772 U.S. counties. Bleidorn and colleagues compared 860 U.S. cities on the Big Five and observed significant variation within states, with cities having more in common with similar sized cities from other states than with other smaller cities in their own state (Bleidorn, Schönbrodt, Gebauer, Rentfrow, Potter, and Gosling, 2016). Rentfrow and colleagues examined 380 Local Authority Districts (LADs) in Great Britain and found distinct geographical patterns for certain traits. And Jokela, Bleidorn, Lamb, Gosling, and Rentfrow (2015) observed personality clusters across 216 London postal districts, which span just over 240 square miles.

In addition to mapping the geographical distribution of the Big Five, several studies have investigated the ways in which regional personality differences relate to important political, economic, social, and health (PESH) outcomes. Results from those studies have revealed evidence that state-level Big Five scores are related to health and morbidity (McCann, 2010a, 2010b; Pesta, Bertsch, McDaniel, Mahoney, & Poznanski, 2012; Voracek, 2009), psychological well-being (McCann, 2011; Pesta, McDaniel, & Bertsch, 2010; Rentfrow, Mellander, & Florida, 2009), social capital (Rentfrow, 2010), creative capital (Florida, 2008), income inequality (de Vries, Gosling, & Potter, 2011), entrepreneurship rates (Obschonka et al., 2013), innovation (Lee, 2017), political values (Rentfrow et al., 2009), regional stereotypes (Rogers & Wood, 2010), and economic hardship (Matz & Gladstone, 2018). The results strongly suggest that the psychological characteristics that are common in a population are linked to important PESH outcomes.

Research in geographical psychology has identified a number of potentially important directions for future research. Indeed, by offering a broad conceptualization of the environment that includes neighborhoods, cities, and regions, research in this area has the potential to shed new light on the ways in which psychological processes and environmental factors interact and impact individuals. However, despite this potential, caution is warranted because much of the findings in this area are based on false assumptions and ill-suited data analytic techniques.

Limitations of Past Work on Geographical Differences in Psychology

Research in geographical psychology has typically applied conventional OLS regression analyses on one level of spatial aggregation (e.g., countries, states, counties). Although such analyses are suitable for examining most group-level comparisons, the observations examined in geographical psychology are spatial in nature and require analytical techniques designed for spatial data. Indeed, when working with spatial data, at least two critical questions must be considered: (1) How are spatial entities defined? (2) How are spatial dependencies within the data managed?

Defining spatial entities. All previous studies of geographical variation in personality have picked one level of spatial aggregation (e.g., states within the U.S.) and then reported the correlations between aggregated personality scores and PESH outcomes only for that specific level. However, the question of how to divide a given geographical space into smaller components is crucial, and different levels of spatial aggregation can yield drastically different results. It is well known in geographical information science that results can change according to the level of aggregation, and is referred to as the Modifiable Aerial Unit Problem (MAUP). The MAUP describes the fact that "when spatial data are aggregated, the results are conditional on the spatial scale at which they are conducted, and the configuration of the areal units that are employed to represent the data" (Manley, 2014, p. 1157). In other words, the relationship between two spatially aggregated variables may change in response to the number (scaling effect) and shape (zoning effect) of entities into which a space is decomposed. There are several studies showing that the choice of aerial units can have drastic effects on the results (Amrhein & Flowerdew, 1992; Openshaw & Taylor, 1979). A well-known real-life example for the relevance of the MAUP is political gerrymandering, a process in which an area is decomposed into electoral districts in a way that one party gains an advantage by diluting the voting strength of another party (Balinski, 2008). Correspondingly, Kirby and Taylor (1976) show that a single pattern of individual votes can lead to different area results depending on the level of scale. Another example how the definition of spatial entities can affect results are geographic boundaries that create a division between the spatial entity to which a person is assigned and the spatial entity in which the person's relevant actions take place (Kwan, 2012). For example, consider the frequent case in which administrative borders separate a city from its surrounding residential areas. Although the majority of people's daily interactions (work, leisure, etc.) may occur within the city, a large proportion of people may live in neighborhoods located in different administrative areas.

Taken together, to assess the meaningfulness and robustness of a relationship between two spatially aggregated variables requires "an approach whereby multiple scales of measurement and analysis should be considered" (Manley, 2014, p. 1170). However, so far no study has examined the correlates of regional personality differences across multiple levels of aggregation. Accordingly, it is unclear whether correlates of regional personality differences are generalizable or rather specific to certain levels.

Managing spatial dependencies. Previous studies have largely examined the correlates of regional personality differences without considering potential spatial dependencies in the underlying data. However, neglecting spatial dependencies can violate the assumptions underlying most statistical procedures. In a broad sense, spatial dependencies are a representation of Tobler's first law of Geography, which states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970,

p. 236). In fact, psychologists already know that dependencies between observations involve statistical assumptions that are not addressed in traditional multivariate analyses. For example, when studying students from different classes within a school, psychologists would use multi-level models to account for the nesting of students in different classes (Koth, Bradshaw & Leaf, 2008). Likewise, in time series data (i.e., repeated measures of a variable at different time points) psychologists would use temporal autoregressive terms to account for the fact that the state of a variable may depend on that variable's prior states (Jebb, Tay, Wang & Huang, 2015). Importantly, similar problems arise when working with spatial data. For example, consider again the previously outlined example in which administrative boundaries separate a city from its suburbs. If we were interested in the link between regional agreeableness and crime rates, we might expect that much of the crime behavior of suburban residents actually takes place in the city's core. Consequently, crime rates in the core city may not only depend on the levels of agreeableness within the core city itself, but also on *spill-over effects* from the level of agreeableness in the suburbs. From a statistical point of view, if spatial dependencies (i.e., greater similarity among proximal spatial entities) are not fully explained by the included variables, the unaccounted spatial pattern will become part of the error term (De Knegt et al., 2010). This so-called *spatial autocorrelation* among the error terms hence violates the assumption of independent residuals and increases the chance of false positives (Type I errors)[3].

Taken together, to assess the meaningfulness and robustness of a relationship between two spatially aggregated variables it is important to test for the presence of spatial autocorrelation among error terms. However, previous psychological research has largely neglected the spatial nature of the data in their statistical analyses. Specifically, to our

[3] Given that spatially autocorrelated error terms are not fully independent, they do not add a full degree of freedom. Such an inflation of degrees of freedom increases the chance of rejecting a true null hypothesis (Legendre, 1993) and can lead to biased or even inverted parameter estimates (Bini et al., 2009). This holds true not only in OLS regressions, but also for Pearson correlation coefficients (Haining, 2010).

knowledge, only three studies concerned with regional psychological differences have checked for spatial dependencies among error terms (Ebert et al. 2019; Matz & Gladstone, 2018; Webster & Duffy, 2016). Accordingly, it is conceivable that, at least some of the observed correlates of regional personality scores and PESH indicators were artifacts of spatial dependencies within the data. These considerations obtain even more importance given that previous research actually reported nearby regions being more similar in personality than distal regions as a central finding of their study (Rentfrow et al., 2013, 2015).

Present Research

Past research suggests that personality traits are geographically clustered and associated with important macro-level outcomes, but the confidence with which we can generalize from that research is limited by the reliance on statistical methods that are ill-suited for analyzing spatial data. Therefore, it is unclear whether the findings from previous research persist when rigorously accounting for the spatial nature of the data. Thus, the primary goal of the current research was to assess regional variation in personality using data analytic techniques that account for the peculiarities of spatial data.

To achieve our goal, we investigated regional personality differences in the U.S. and in Germany using methods and analytical techniques that are designed to handle spatial data. Specifically, for both countries, we (1) applied a cutting-edge mapping approach that allows for the depiction of spatial distributional patterns without aggregating zip code information to the regional level, (2) based all our correlational analyses on three different levels of spatial aggregation, and (3) applied spatial econometric techniques in our correlation analyses to account for spatial dependencies in the data.

Study 1

Several studies have examined regional differences in the Big Five. Those studies have focused on one level of spatial analysis only, including large multi-state regions, U.S. states, cities or neighborhoods (Bleidorn et al., 2016; Jokela et al., 2015; Rentfrow et al., 2008; 2015). Furthermore, the results from that research suggest that regional differences in the Big Five are associated with a range of important PESH outcomes, from votes in political elections and economic innovation, to violent crime and disease death rates (Lee, 2017; McCann, 2010a, 2010b, 2011b; Obschonka et al., 2013, 2015, 2018; Pesta et al. 2012; Rentfrow et al., 2008, 2015). However, no previous study in this area has investigated multiple spatial levels simultaneously, and only very few studies have controlled for spatial dependencies in the data. In other words, questions about MAUP, and statistical artifacts remain largely unaddressed. It is therefore possible that findings from previous research do not hold up when analyzed using methodological and statistical techniques designed to handle spatial data.

The overarching aim of Study 1 was to evaluate the reliability of existing findings using rigorous methodological and analytical techniques that are designed for working with spatial data. Specifically, using data from a large sample of U.S. residents, the study was designed to: (1) visualize distributional patterns that are not diluted by predefined spatial entities, (2) address the MAUP in regression analyses by examining geographical variation in personality across multiple levels of spatial analysis, and (3) manage spatial dependencies in regression analyses by spatial econometric approaches that are intended for spatial data.

Data

Regional Personality Data

To address the aims of the investigation, we used data from the Gosling-Potter Internet Personality Project (GPIPP; Gosling, Vazire, Srivastava, & John, 2004). Participants could find the website in different ways, for example through links on other websites or search engines. For the present investigation, we only included participants who completed the personality measure, were between 15 and 70 years of age, reported living in the U.S. and provided a valid zip code. After applying the selection criteria, the sample included 3,387,303 participants who completed the survey between 2005 and 2015. Consistent with previous Internet-based research (Gosling et al., 2004) and previous studies using GPIPP data (e.g., Rentfrow et al., 2008), the demographic composition of the sample showed an overrepresentation of women (65%) and younger people (M_{age} = 27.02, SD = 11.75).

Personality was assessed using the Big Five Inventory (BFI) (John, Donahue, & Kentle, 1991; John & Srivastava, 1999), which consists of 44 items that contain short phrases of prototypical markers of each dimension: extraversion, agreeableness, conscientiousness, emotional stability, and openness. Participants reported the degree to which they agreed with each statement using a 5-point rating scale (ranging from 1 = *Disagree strongly* to 5 = *Agree strongly*). After completing the survey, participants received a customized evaluation of their personalities. Participants gave their consent to take part by proceeding to the study through clicking on a link. Table 1 reports descriptive statistics for the individual BFI scores. Cronbach's α scores for the five scales ranged from .80 .to .87 indicating sufficient reliability. A Principal Component Analyses with varimax rotation suggested five factors and each item had its highest loading onto its referring latent trait. Online Supplement 1 reports an overview of all items and their factor loadings.

Table 1

Descriptive Statistics and Psychometric Properties of the Underlying Personality Data in the U.S.

Trait	*N*	*M*	*SD*	α	ICC2 2,547 Counties	ICC2 908 CBSAs	ICC2 49 States
Extraversion	3,387,303	3.39	0.84	.87	.76	.85	.98
Agreeableness	3,387,303	3.78	0.67	.81	.86	.92	.99
Conscientiousness	3,387,303	3.59	0.71	.84	.87	.93	.99
Emotional Stability	3,387,303	3.10	0.82	.85	.84	.91	.99
Openness	3,387,303	3.67	0.66	.80	.95	.97	.99

Note: CBSA = Core-based statistical area.

We used zip code information to assign each participant to one of 3,106 counties within the contiguous U.S. (i.e., 48 adjoining states plus the District of Columbia). For zip-code areas that belong to multiple counties, we assigned participants to the county with which the zip code area shares the largest population overlap. In a next step, we assigned each county to 1 of 909 core-based-statistical areas (CBSAs). CBSAs are functional spatial entities consisting of an urban core of at least 10,000 inhabitants plus an adjacent hinterland with strong economic and social ties to the core area.[4] Finally, we assigned each county to one of 49 states of the contiguous U.S., thereby including the spatial level in our analyses that has been most widely applied in previous research (e.g., de Vries, Gosling, & Potter, 2011; Elleman, Condon, & Revelle, 2018; McCann, 2010a, 2010b; 2011; Rentfrow et al., 2008, 2013; Voracek, 2009). After assigning each participant to their referring entities, we excluded all spatial entities with less than 50 observations.[5] This minimum threshold eliminated 559

[4] CBSAs are demarcated based on commuting patterns and can span across administrative boundaries, e.g. consist of counties belonging to different states. Hence, they are an attempt to form regions in which employees both live and work (Andersen, 2002; Cörvers, Hensen, & Bongaerts, 2009; OECD, 2002), thereby representing the daily available interaction space. Importantly, CBSAs only cover areas of the U.S. that feature a connection to an urban core, and thus exclude purely rural areas. More specifically, CBSAs cover 55% of the surface and 94% of the population of the contiguous U.S.

[5] In research dealing with subnational personality differences a common approach to address the problem of small regional samples is to exclude those regions with sample sizes that fall below a specified threshold (e.g. 200 in Bleidorn et al., 2016 or 100 in Gebauer et al., 2017 or 50 in Matz & Gladstone, 2018). In the light of the present research goal, we decided to apply the rather loose threshold of 50 observations per region for the following reasons: First, excluding regions would lower the statistical power of our regression analyses. Second, removing regions with the smallest sample sizes would selectively exclude rural and thinly populated areas. Excluding these regions could challenge the generalizability of our findings, as the remaining subsample of regions no longer represents the whole spectrum of regions. Finally, analyses of spatial dependencies address

entities (out of 3,106 in total) and 1 CBSA (out of 909). The regional samples were highly representative of the actual number of inhabitants per region. The correlation between regional sample size and regional population was .96 for the 2,547 counties, .97 for the 908 CBSAs and .98 for the 49 states.

Finally, we conducted psychometric analyses to examine the suitability of the underlying personality data for geographical analyses following the approach suggested by Rentfrow et al. (2015). First, we checked for metric and scalar invariance across regions using multi-group factor analyses. Specifically, we compared the factor structure in a given region (first group) to the factor structure in the remaining regions (second group). Comparative fit index deviations between groups greater than .01 were treated as a violation of invariance (Cheung & Rensvold, 2002). To reduce the number of models, we fitted these analyses only on the medium level of 908 CBSAs. With 908 regions × 5 traits × 2 invariance conditions, this led to 9,080 tests of invariance, of which none exceeded the threshold of .01. Second, to gauge the degree of sampling error in the regional samples, group-mean reliabilities (also called intraclass correlation 2, ICC2; Bliese, 2000) of the aggregated traits were examined (see Table 1). Overall, group mean reliabilities were in an acceptable range between .76 and .99. Reflecting the smaller sample sizes at finer spatial levels, group mean reliabilities were perfect at the state level (ranging from to .98 to .99) and lowest for the county level (ranging from .76 to .90). To address the problem of increased sampling error at finer levels, we based regional personality scores for the county and CBSA level on *Best Linear Unbiased Predictors (BLUPs)* instead of raw means. BLUP scores are linear combinations of random effects that can be used to predict group-specific random effects.

the relationship between regions and their neighbors, therefore removing a region would have effects on the neighboring regions.

Robinson (1991) shows that this approach minimizes the mean squared error of the estimation.

PESH Indicators

To assess the reliability and robustness of the correlates of regional personality scores, we obtained data for PESH indicators across three levels of spatial aggregation. The selection of variables followed Rentfrow et al.'s (2008, 2015) earlier selection of PESH indicators. Given that the personality data were collected between 2003 and 2015, we tried to measure these PESH indicators in the middle period of data collection. Furthermore, we tried to minimize the impact of annual fluctuations by aggregating data across multiple years.

Demographic indicators. To capture the demographic composition of the regions, regional estimates for gender, median age, and percentage of foreign born (based on possession of citizenship) were gathered. The variables are 5-year estimates (2008-2012) from the American Community Survey (ACS, United States Census Bureau, 2012)

Political indicators. Data addressing the regional political opinion comprised the share of votes for the republican candidate in the presidential elections of the years 2008 and 2012 (MIT Election Data and Science Lab, 2018).

Economic indicators. Regional prosperity is described by the average median income of the years 2008 to 2012 (United States Census Bureau, 2012). To capture the creative and innovative potential of regional economies (Griliches, 1990), the average number of patents per 1,000 employees between 2000 and 2010 was calculated based on data obtained from the United States Patent and Trademark Office (USPTO) database (Li et al., 2014). Information regarding the residency of the inventor was utilized to spatially aggregate the data.

Social indicators. To measure the social stability of regions, the share of married residents was included. As a differentiation between urban and rural communities/lifestyles, population density was included as a measure of urbanization. Both of these variables represent 5-year estimates of the 2012 ACS (United States Census Bureau, 2012). To capture the level of criminal activities, the average number of incidents of violent crime per 1,000 for the years 2010-2012 was obtained (United States Department of Justice, 2014). Finally, to measure the degree of social capital in a region, we included the Northeast Regional Center for Rural Development's (2014) index of social capital, representing the presence of clubs and associations in the region in the year 2014.

Health indicators. Regional health levels were measured by the life expectancy of a child born between 2010 and 2014 in the corresponding region (Institute for Health Metrics and Evaluation, 2019).

Human capital. Regional human capital was represented by educational, occupational and industrial information (5-year estimates) from the 2012 ACS. Education was depicted by the average share of employees holding a university degree. Occupational statistics were based on the Standard Occupational Classification (SOC; U.S. Department of Labor, 2000). Specifically, we differentiated between the share of employees in managerial & professional occupations, as well as trade & elementary occupations. Additionally, to capture the creative potential of a region, a measure indicating the share of employees in the arts, entertainment and recreation sector was included.

Methods

Visualizing regional personality differences. We applied a newly developed mapping approach (Brenner, 2017) to examine the spatial distribution of personality traits across regions. Our approach is able to depict spatial patterns without aggregating to a higher level of analysis. As a result, we are able to avoid most of the challenges associated with MAUP in our mapping approach.

For the present study, we used very fine-grain zip code data to apply a region-free approach for the identification of clusters. That is, we calculated the average score for each

Big Five personality trait for each zip code. For this calculation, we did not only use data from participants who lived in the referring zip-code area, but based the calculation on the complete sample. Specifically, the Big Five scores of all participants were included, but participants' scores were weighted according to their distance to the corresponding zip code area. To this end, we calculated the "bee-line distance" between all 30,817 × 30,817 pairs of zip codes. Finally, to transform the bee-line distance into weights, a log-logistic distance decay function was applied, given by:

$$f(d) = \frac{1}{1 + \left(\frac{d}{r}\right)^{s}} \tag{1}$$

,where *d* denotes the bee-line distance between zip-code areas. The parameter *r* denotes the distance at which the decay function reaches a value of ½ and *s* determines the slope of the decay with distance. Various studies show that commuting or travelling for short-term activities is perceived as cumbersome if it exceeds 60-80 minutes one-way (Ahmed & Stopher, 2014), which translates into a physical distance of 35 to 50 miles (Phibbs & Luft, 1995). Therefore, we set $r = 45$ miles and chose s to be 7.

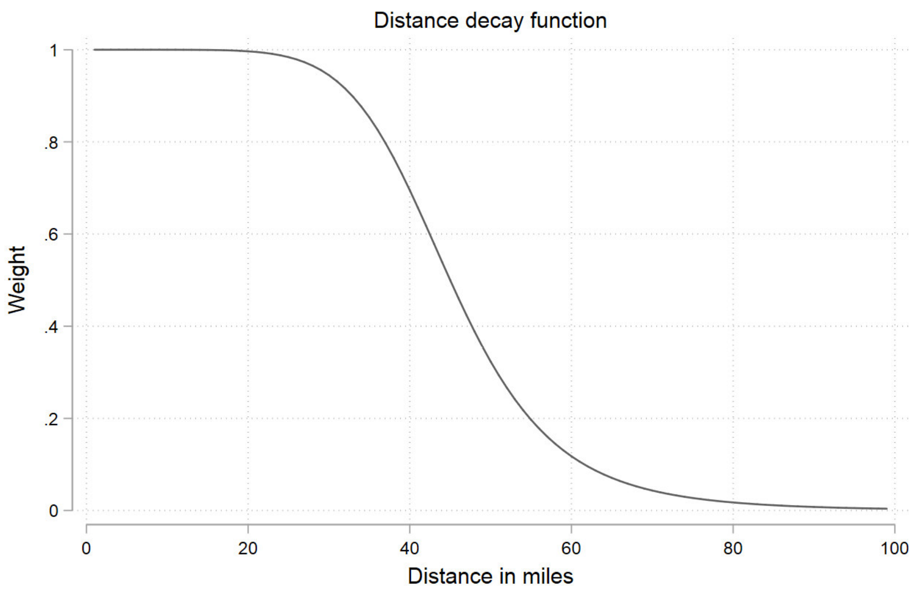

Figure 2. Shape of the employed distance decay function in the U.S.

Figure 2 shows that setting these parameters led to a distance decay function in which participants up to a distance of 30 miles receive a weight of nearly one. In contrast, participants with a distance of 45 miles receive a weight of 0.5, and participants further away than 75 miles receive a weight of nearly zero. In this way, our approach for mapping personality allowed for more continuous and nuanced depictions of the Big Five that reflect the spatial range of human activities and are not constrained by arbitrary administrative boundaries.

Addressing the MAUP in the correlates of regional personality. To address the extent to which previous results are prone to the MAUP, we investigated the patterns of associations between aggregate personality scores and PESH indicators across multiple levels of aggregation. We used a pragmatic approach that (a) aligns with the spatial levels used in previous psychological research and (b) psychologists can readily integrate in their workflow and methodological environment without additional costs.[6] To make our results comparable to previous studies, we first ran conventional OLS linear regressions using regional personality as dependent variable. We did this across the three previously described regional levels (counties, CBSAs, states) and then compared the results from these levels to each other. To rule out that the revealed correlates of regional personality are merely a reflection of demographic and urban/rural differences, we followed Rentfrow et al. (2008, 2015) and controlled for gender, median age, median income, percentage of African Americans and urbanity (population density). All variables were *z*-standardized to ease the interpretation of effect sizes.

Managing spatial dependencies in the correlates of regional personality. In a second step, we addressed the challenges associated with spatial dependencies in the data.

[6] For more sophisticated and complex approaches to address the challenges of the MAUP see, e.g., Hui, 2009 or Openshaw, 1979.

Specifically, we tested spatial dependencies among the residuals of the OLS linear regression models for all three spatial levels. To gauge how far the assumed independence of residuals was violated, Moran's I tests were applied (Moran, 1950; Tiefelsdorf & Boots, 1995). Moran's I tests allow for evaluating whether proximal regions exhibit more similar personality scores than distal ones. Assessing such spatial dependencies first requires quantifying the spatial relation between regions via a so-called spatial-weight matrix (Arbia, 2014). Generally, the relation between spatial entities can be operationalized in a variety of ways. The most widely used approach is to operationalize proximity based on adjacency, that is, whether or not two regions share a border.[7] In the present research, we follow this most common approach and base our matrix on the definition of Queen's adjacency, resulting in a binary weighting matrix in which each cell indicates whether two regions share a border or not.[8]

To account for existing spatial dependencies in statistical models, the spatial econometric literature provides different approaches to re-specify OLS linear regressions. These approaches can broadly be differentiated in spatial error models and spatial lag models or combinations of both (Arbia, 2014). Spatial error models treat spatial dependency as a form of nuisance. This nuisance is then eliminated by adding a spatially weighted component in the error terms. In contrast, spatial lag models add spatially lagged values of the dependent variable to the right-hand side of the equation. Accordingly, the included spatial lags exert a direct influence on the dependent variable and thereby give spatial dependencies a substantive interpretation (Anselin & Rey, 1991). For example, consider again the previous

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[7] Alternatives to this definition include using the inverse distance between two regions or identifying a given number of entities that are closest to the target entity, e.g. the five nearest neighbors of a given region (see Getis & Aldstadt, 2004 for a full discussion).

[8] In a few instances, some of the counties and CBSAs do not share a border with any other region because 1) the sample size inclusion criteria forced us to exclude a few counties and CBSAs and 2) CBSAs do not generally cover the entire surface of the U.S.. For such borderless regions, we instead used the geographically closest region (bee distance), thereby ensuring that each region had at least one neighbor. To ensure equal proportional weights for all regions, the matrix was row standardized via dividing the binary adjacency information by the total number of neighbors for that region.

example on the relationship between agreeableness and crime behavior. By including spatially lagged values of agreeableness, we could evaluate to what degree the relationship between crime behavior and agreeableness can be explained by the levels of agreeableness in neighboring regions. Adding spatially lagged values can, thus, be understood as an equivalent to a temporal autoregressive term in time series analyses. The inclusion of the spatially lagged values allows evaluating how far the value of a variable of interest in one location is determined by this variable's values in other locations. As we did not want to treat spatial dependencies only as a form of nuisance, we favored fitting a spatial lag model. We nevertheless also tested spatial error models (see later) and found that a spatial lag model performed significantly better in accounting for spatial dependencies in our data.

Results and Discussion

Spatial distribution of personality within the U.S. Our first objective was to evaluate the spatial distribution of personality traits in a way that minimized challenges associated with MAUP. To do so, we used a mapping approach that allowed spatial patterns to emerge freely from the data without being diluted or constrained by administrative boundaries. As a result, the geographical clusters that emerge from the data should adequately reflect the true boundaries of distinct psychological contexts.

The spatial distribution of the Big Five can be seen in Figure 3. The maps reveal a number of similar patterns across traits and also specific patterns for each trait. Across all traits, it is particularly striking that many areas exhibit clustering of similar scores. In many cases, distinct spatial clusters appear quite intuitive, as the referring area shares important commonalities (e.g., the Deep South or the New England states), and in many cases, the spatial clustering of traits spans across administrative boundaries, such as in Tennessee and its adjacent states. Another common finding across all the traits is that the spatial clustering is not uniform within administrative boundaries. That is, even states that are often referred to as prototypical examples of a certain regional culture – such as progressive California or conservative Texas – are not homogeneous, but actually consist of very different psychological contexts. For example, central California significantly deviates from the rest California on almost every trait. And in Texas, cities like Austin and Dallas form islands with personality profiles that are very different from the rest of the state.

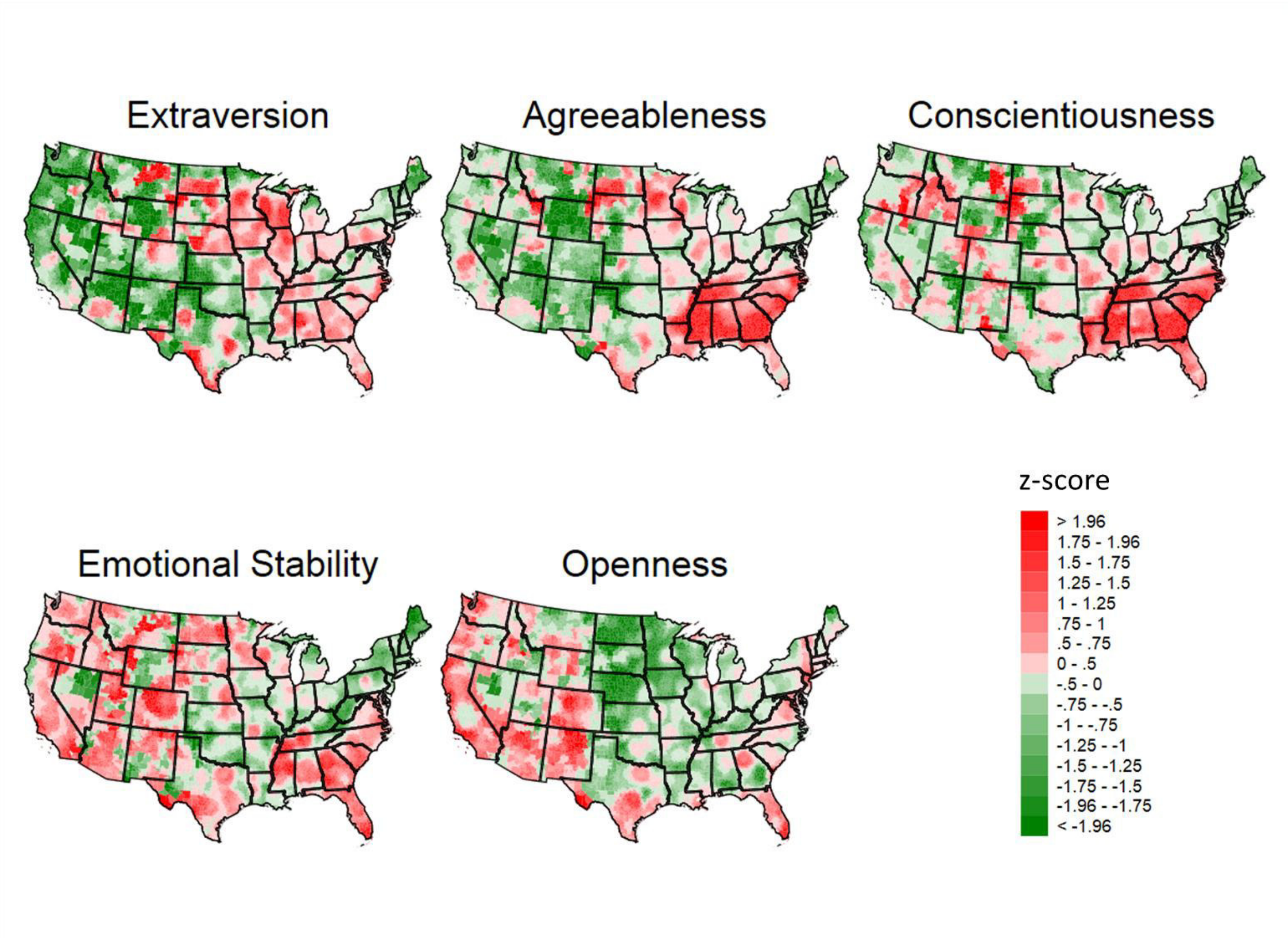

Figure 3. Mapping regional personality differences in the U.S

Each trait also showed a unique geographical pattern. For example, extraversion appears to be higher in the Southwest, the Rust Belt and the central Northern states, as well as in pockets of the South. Large areas with comparatively low levels of extraversion emerged in the West, parts of the Southwest as well as in New England. The spatial distribution for agreeableness shared some similarities with extraversion. Large areas with significant clustering of high levels of agreeableness were found in the Southwest, the Rust Belt, the Midwest, and in pockets of the West and Southwest. Low levels of agreeableness emerged in the West and the New England states. For conscientiousness, higher average scores clustered in the Southwest, while the New England states formed a cluster of comparatively low average scores. The rest of the U.S. forms a fragmented patchwork of areas with high and low scores of conscientiousness. Higher levels of emotional stability were observed in large parts of the West as well as in the South-West, whereas comparatively low levels were observed in the North-East and central parts of the U.S. For openness, there appears to be an East-West divide, with regions in the West generally showing slightly higher levels of openness than the East, with the exception of Florida, and comparatively low levels of openness in the central and eastern parts of the U.S. Another striking pattern for openness is that the large swathe of low openness is broken up by major metropolitan regions, such as Atlanta, Nashville, Kansas City, Chicago, Washington D.C., and New York City.

Taken together, the distributional patterns of personality presented here highlight the merits of our new mapping approach and provide unprecedented insights into the spatial distribution of personality within the U.S. Indeed, by minimizing the problems associated with MAUP, the mapping approach revealed spatial clusters of personality traits that would have been disguised by imposing prefixed administrative boundaries. As such, the maps presented here offer a significant advancement over previous research concerned with regional personality differences in the U.S. by revealing systematic geographical differences between and within administrative boundaries.

Correlates of regional personality across three spatial levels. Our second objective was to investigate the degree to which associations among regional personality and PESH indicators are prone to the MAUP. Table 2 reports the correlations between the personality and PESH indicators for counties, CBSAs, and states when partialling out gender, median age, income, race, and urbanity. Overall, the patterns of associations across the different levels of analysis largely match the results observed in previous studies in the U.S. (Rentfrow et al., 2008). Effect sizes were generally largest at the state level and smallest at the county level – a typical pattern in studies investigating correlates across multiple levels of aggregation that is due to the smaller number of observations at higher levels of aggregation (Manley, 2014). A closer inspection of the PESH correlates across three spatial levels also revealed the degree to which the correlations from a specific spatial level generalized across different levels of spatial aggregation.

At the county level, extraversion showed the strongest positive correlations with the share of foreign born and the strongest positive correlation with life expectancy. These two relationships also generalized to the CBSA and state levels (i.e., across all three spatial levels). Weaker positive correlations were found for the share of married residents and the social capital index, while a weaker negative correlation was found for patents and violent crimes. While all these relationships also generalized to the CBSA level, none generalized to the state level.

Table 2

Correlates of Regional Personality Scores across Three Spatial Levels in the U.S.

Variable / Trait	Extraversion			Agreeableness			Conscientiousness			Emotional Stability			Openness		
	2,547 counties	908 CBSAs	49 states	2,547 counties	908 CBSAs	49 states	2,547 counties	908 CBSAs	49 states	2,547 counties	908 CBSAs	49 states	2,547 counties	908 CBSAs	49 states
Foreign born	**-.13**	**-.14**	**-.29**	**-.08**	-.03	-.32	**-.12**	**-.08**	-.19	**.14**	**.19**	.12	**.36**	**.32**	**.76**
Republican 2008	.03	.04	.11	**.10**	.05	**.46**	**.13**	**.13**	.26	**-.09**	**-.07**	-.17	**-.23**	**-.25**	**-.67**
Republican 2012	**.05**	.06	.19	**.10**	.05	**.47**	**.14**	**.13**	**.31**	**-.09**	**-.07**	-.19	**-.25**	**-.27**	**-.75**
Manager &Profess.	.01	-.06	.00	**-.05**	-.02	-.50	**-.05**	-.06	.13	**.25**	**.19**	**.47**	**.40**	**.39**	**.64**
Trade & Elementary	.00	.04	.29	**.07**	.04	**.53**	.00	.03	.01	**-.24**	**-.25**	**-.37**	**-.48**	**-.44**	**-.89**
University degree	.03	.01	.02	**-.06**	.03	-.47	-.04	-.03	.14	**.42**	**.39**	**.64**	**.64**	**.54**	**.81**
Creatives	-.01	.01	-.28	**-.05**	-.01	**-.36**	.03	.04	-.11	**.18**	**.21**	-.06	**.34**	**.32**	**.50**
Patents	**-.06**	**-.13**	-.13	-.01	.01	.25	**-.06**	-.04	.00	.03	.01	.09	**.11**	.07	.07
Life expectancy	**.13**	**.25**	**.52**	.04	**.17**	.40	.00	.02	.13	**.43**	**.52**	**.89**	**.15**	**.18**	.17
Married	**.09**	**.11**	.30	**.18**	**.10**	**.84**	**.23**	**.24**	**.34**	.00	-.01	.03	**-.52**	**-.39**	**-.88**
Violent Crimes	**-.08**	**-.10**	-.21	.00	.03	.02	.00	-.03	.00	.03	.02	-.16	**.17**	**.10**	.08
Social Capital Index	**.07**	**.12**	.19	.00	.05	**-.30**	**-.04**	.00	-.09	**.15**	**.08**	.04	**-.09**	**-.18**	-.04

Note: Bold values indicate significance at the 5%-level. CBSA = Core-based statistical area.

For agreeableness, the strongest correlation that emerged was a positive relationship with the share of married residents. This relationship generalized across all three spatial levels. Weaker positive associations were found with republican votes and trade & elementary professions, while weaker negative associations emerged for the share of foreign born, managerial professions, the share of people with university degrees and creative industries. Of these relationships, the majority could be replicated at the state level, but none of these relationships was found at the CBSA level. At the CBSA level an additional positive correlation emerged for life-expectancy.

The strongest positive correlates of conscientiousness were found for republican votes and the share of married residents, while the strongest negative correlation was found for the share of foreign born. Apart from the share of foreign born, all these relationships generalized across all three spatial levels. Weaker negative associations were found for managerial professions, patents and the social capital index, however none of these relationships was found at the CBSA or state level.

Emotional stability showed the strongest positive relationships with high status professions, the share of people with university degrees and life expectancy. The strongest negative correlations were found for trade & elementary professions. All of these relationships generalized across all three spatial levels. Weaker positive correlations were found for the share of foreign born, the share of people with university degrees and the social capital index, while weaker negative correlations emerged for republican votes. All of these relationships generalized to the CBSA level, but none was found at the state level.

Openness was significantly related to all indicators at the county level. The strongest positive correlations were found for the share of foreign born, managerial professions, the share of people with university degrees and creative industries. The strongest negative associations emerged for republican votes, trade & elementary professions and the share of married residents. All of those relationships generalized across all spatial levels. Weaker positive correlations were found for patents and life expectancy and weaker negative correlations were found for the social capital index. The relationships for life expectancy and the social capital index also generalized to the CBSA level, but none of the weaker relationship were found at the state level.

Taken together, the analyses yielded mixed results: Some of the regional personality correlates generalized across all three spatial levels, while others did not. The largest number of statistically significant results was found on the county level. Of those county level relationships, the strongest ones usually generalized across all three spatial levels, that is, speaking for true and substantive relationships between these variables. Accordingly, the county level, which has greater statistical power (N = 2,547), is most sensitive in detecting statistically significant correlates of regional personality scores. In fact, almost every significant correlation on the CBSA or state level was also significant at the county level. Consequently, our findings suggest that relationships at the CBSA or state level found in previous studies would very likely also replicate at the county level. Importantly, when going from the county level to higher spatial levels, there emerged no significant change in sign (i.e., a positive significant relationship turning to a negative significant relationship, or vice versa). In other words, the relationships between regional personality scores and PESH outcomes generally tend to be consistent across the three spatial levels. However, our findings also highlight the importance of investigating the correlates of regionally personality scores across multiple levels. Specifically, studies reporting effects of small magnitude on fine-grained levels like counties might have arrived at different conclusions if different spatial levels were analyzed.

Managing spatial dependencies among error terms. In the previous step, we have reported the correlates of regional personality differences and examined how they generalize across multiple spatial levels. In line with existing research, we did so using conventional OLS linear regression models. However, we did not yet account for spatial dependencies in the data, which – as outlined previously - can lead to biased or even inverted estimates. Therefore, our third objective was to assess the extent to which the observed correlates of regional personality hold when accounting for spatial dependencies. In a first step, we used Moran's I tests to assess the degree of clustering for the regional personality scores. Table 3 reports that for all five traits across all three levels, there occurred highly significant spatial clustering (i.e., neighboring regions showing more similar scores) of medium to large magnitude. Next we checked how much of that spatial clustering remained among the residuals of our regression models (i.e., when accounting for the referring predictor and the complete set of control variables). In a final step, we accounted for spatial dependencies by adding spatial lags to our models and examined the extent to which the inclusion of these spatial lags changed the results of the OLS models. For reasons of parsimony, we only discuss the results for the county level – the finest spatial level that also showed the largest number of significant correlations in our previous models. The results for the CBSA and state level are reported in Online Supplements S2 and S3. For both spatial levels, the results and drawn conclusions are conceptually similar to the county-level results.

Table 3
Spatial Clustering of Big Five Personality Traits across three levels in the U.S.

	2,547 counties		908 CBSAs		49 states	
Trait	Moran's *I*	*p*	Moran's *I*	*p*	Moran's *I*	*p*
Extraversion	.19	.00	.25	.00	.36	.00
Agreeableness	.44	.00	.47	.00	.55	.00
Conscientiousness	.38	.00	.39	.00	.72	.00
Emot. Stability	.35	.00	.33	.00	.52	.00
Openness	.41	.00	.34	.00	.32	.00

Note: CBSA = Core-based statistical area.

The second column for each trait in Table 4 reports the results of the Moran's I tests for the residuals of the OLS models. These tests revealed highly significant spatial autocorrelation of small to moderate magnitude for all five traits. In other words, the residuals of the regression models violated the underlying assumption of independency in the sense that neighboring regions generally tended to exhibit more similar residuals than non-neighboring ones. Next, we included spatially lagged values of regional personality scores into our regression models. We then again conducted Moran's I tests for the residuals of these spatial lag models. The fourth column for each trait in Table 4 reveals that including spatial lags (almost) entirely captured any existing spatial dependencies for conscientiousness and emotional stability. Accordingly, the error terms of these models no longer violated the underlying assumption of residual independency. Significant autocorrelation among the residuals remained for agreeableness and some models of extraversion and openness (i.e., the traits that show the greatest degree of geographical clustering, see Table 3). However, although the spatial autocorrelation among some of the residuals for these two traits was still significant at the 5%-level, the magnitude of spatial autocorrelation decreased greatly. Accordingly, only a tiny fraction of autocorrelation was still left, which is not strong enough to impose any severe problems. Taken together, the results strongly supported the choice of the spatial lag model, as this approach could almost completely capture any existing spatial dependencies among the residuals.[9] To scrutinize the choice of our spatial econometric approach, we repeated all our analyses using a spatial error instead of a spatial lag model. Corroborating our model choice, Online Supplement S4 shows that a spatial error model could not account for the spatial autocorrelation among error terms.

9 The conclusion of no spatial dependencies in the error terms is naturally limited insofar as it only refers to the type of spatial dependencies modeled by the underlying spatial weight matrix. Accordingly, it cannot be completely ruled out that there remain spatial dependencies within the data that are not captured by the applied definition of adjacency.

Table 4

Correlates of County-Level Personality Scores in the U.S. when accounting for Spatial Dependencies.

Variable / Trait	Extraversion				Agreeableness				Conscientiousness				Emotional Stability				Openness			
	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc
Foreign born	**-.13**	**.18**	**-.10**	-.01	**-.08**	**.22**	**-.04**	**-.03**	**-.12**	**.21**	**-.08**	-.01	**.14**	**.25**	**.09**	.01	**.36**	**.29**	**.21**	-.02
Republican 2008	.03	**.18**	.03	-.01	**.10**	**.22**	**.04**	-.02	**.13**	**.21**	**.08**	-.01	**-.09**	**.27**	**-.08**	.00	**-.23**	**.38**	**-.18**	.00
Republican 2012	**.05**	**.18**	**.04**	-.01	**.10**	**.22**	**.04**	**-.02**	**.14**	**.21**	**.08**	-.01	**-.09**	**.26**	**-.08**	.00	**-.25**	**.38**	**-.19**	-.01
Manager &Profess.	.01	**.18**	.04	-.01	**-.05**	**.22**	-.03	**-.03**	**-.05**	**.22**	-.04	-.02	**.25**	**.27**	**.24**	.00	**.40**	**.37**	**.36**	-.02
Trade & Elementary	.00	**.18**	-.02	-.01	**.07**	**.22**	.03	**-.03**	.00	**.22**	-.01	-.02	**-.24**	**.25**	**-.22**	-.01	**-.48**	**.31**	**-.38**	**-.03**
University degree	.03	**.19**	**.06**	-.01	**-.06**	**.22**	-.01	**-.03**	-.04	**.22**	-.02	-.02	**.42**	**.25**	**.39**	.00	**.64**	**.36**	**.55**	-.01
Creatives	-.01	**.18**	.01	-.01	**-.05**	**.22**	-.02	**-.03**	.03	**.21**	.03	-.02	**.18**	**.25**	**.15**	.00	**.34**	**.30**	**.25**	**-.03**
Patents	**-.06**	**.18**	**-.04**	-.01	-.01	**.22**	.00	**-.03**	**-.06**	**.21**	**-.04**	-.02	.03	**.27**	.03	.01	**.11**	**.36**	**.08**	**-.03**
Life expectancy	**.13**	**.18**	**.11**	-.01	.04	**.22**	**.07**	**-.03**	.00	**.22**	.02	-.02	**.43**	**.22**	**.35**	.01	**.15**	**.38**	**.15**	-.02
Married	**.09**	**.18**	.05	-.01	**.18**	**.20**	**.08**	**-.02**	**.23**	**.21**	**.16**	-.01	.00	**.27**	-.03	.00	**-.52**	**.33**	**-.38**	-.01
Violent Crimes	**-.08**	**.18**	**-.06**	-.01	.00	**.22**	.01	**-.03**	.00	**.21**	.01	-.02	.03	**.27**	.02	.00	**.17**	**.34**	**.10**	**-.02**
Social Capital Index	**.07**	**.18**	**.06**	-.01	.00	**.22**	.02	**-.03**	**-.04**	**.22**	-.03	-.02	**.15**	**.25**	**.12**	.00	**-.09**	**.34**	.00	**-.03**
Average change OLS to spatial model			22%				58%				33%				15%				30%	

Note: Bold values indicate significance at the 5%-level. OLS mod. = OLS model, OLS. autoc. = OLS model autocorrelation, spat. Mod. = Spatial model, Spat. autoc. = Spatial model autocorrelation

Our spatial econometric approach successfully captured existing spatial dependencies, so how did the spatial lag affect the associations between the regional personality scores and PESH indicators? The first column for each trait in Table 4 contains the results of the benchmark OLS linear model. The third column contains the coefficient of the spatial lag model. A comparison between these two columns allows to directly examine the impact of including spatial lags. Most importantly, the majority of correlations that were significant in the OLS model also remained significant when including spatial lags (35 out of 43) – a finding that again speaks in favor of the robustness of regional personality scores and their correlates. However, in some cases previously significant correlations dropped below the 5%-threshold, while new significant correlations emerged. For example, for extraversion the previously significant relationship with married residents was no longer significant in the spatial lag model, while the previously insignificant relationship with university degrees now reach significance. Taken together, in such cases, ignoring spatial dependencies would have produced spurious findings. While for most relationships the previously found significant correlations remained intact, the inclusion of spatial lags consistently decreased the effect sizes. On average, effect sizes for significant OLS relationships shrank by 22% for extraversion, 58% for agreeableness, 33% for conscientiousness, 15% for emotional stability and 30% for openness. Taken together, with most of the previosly relationships remaining intact, the results of the spatial models did not challenge the conclusions of the basic OLS linear models, but rather confirmed their credibility. However, our results also show that ignoring spatial dependencies can lead to spurious correlations in particular cases and an overestimation of true effect sizes in general.

Study 2

Most of the studies concerned with geographical differences in personality have focused attention on the U.S. and on Great Britain (Rentfrow et al., 2008, 2015), but a few studies have examined variation in non-English speaking countries, including Russia (Allik et al., 2009), Germany (Obschonka, Wyrwich, Fritsch, Gosling, Rentfrow, & Potter, 2019), Switzerland (Götz et al., 2018), and China (Wei et al., 2017) . The results from the latter set of studies reveal systematic variation in personality across regions of non-English speaking countries. However, these studies have stopped short of systematically examining the associations between regional personality differences and their associations to important PESH outcomes. Consequently, our understanding of the ways in which regional personality is expressed in PESH outcomes is restricted to the U.S. and Great Britain.

Study 2 aims at studying a country (a) for which large-scale personality data is available, but PESH-correlates of regional personality had not been systematically investigated, (b) whose native language is not English, and (c) whose institutional setting differs from the U.S. and Great Britain. We therefore choose Germany as the study object in Study 2. Besides speaking a different language, Germany's institutional setting (similar to France, Norway, or Sweden) is less market-liberal than the institutional setting in the U.S. or Great Britain (Hall & Soskice, 2001). In addition, Germany appears as a worthwhile study object for a number of reasons: (1) Germany's natural environment covers plain coast landscapes in the North and alpine mountains in the South, (2) regional economic disparities range from some of the most innovative and prosperous regions in the world to seriously deprived areas (Niebuhr, Granato, Haas, & Hamann, 2012), and (3) the country was divided and governed by different political systems for over 40 years, which was followed by a major brain drain from East to West after German reunification (Kröhnert & Vollmer, 2012). Thus, it seems reasonable to not only expect regional differences in personality, but also that those differences will be related to political, economic, societal, and health differences.

To be as consistent with Study 1 as possible, we obtained measures of personality and external PESH indicators that were identical to the corresponding indicator in the U.S. However, in some instances, we had to rely on external indicators that were not identical but conceptually similar to their U.S. equivalent.

Data

Regional Personality Data

To examine regional personality differences in Germany, we used the German subsample (i.e., people residing in Germany) of the GPIPP. We applied the same selection criteria used in Study 1 (i.e., including participants aged 15 to 70 years who completed the personality test and provided valid zip code information). Our final sample included 110,029 participants who completed the survey between 2005 and 2015. Consistent with the characteristics of the U.S. sample, the German sample comprised mostly women (59%) and younger persons (M_{age} = 30.00, *SD* = 11.80). Personality was again assessed on 5-point rating scale, this time via the *German* version of the Big Five Inventory (Rammstedt, 1997). Cronbach's α reliabilities were again in an acceptable range between .74 and .88 (see Table 5) and each item had its highest loading on the referring trait (see Online Supplement S5).

Table 5
Descriptive Statistics and Psychometric Properties of the Underlying Personality Data in Germany

Trait	N	M	SD	α	ICC2 385 ADs	ICC2 251 LMRs	ICC2 96 PRs
Extraversion	110,029	3.41	0.84	.88	.53	.60	.77
Agreeableness	110,029	3.44	0.63	.74	.47	.48	.64
Conscientiousness	110,029	3.45	0.77	.86	.61	.67	.78
Emotional Stability	110,029	3.02	0.86	.87	.48	.58	.74
Openness	110,029	3.75	0.66	.80	.81	.83	.91

Note: AD = Administrative district, LMR = Labor market region, PR = Planning region.

Using the zip-code information provided by participants, we used assignment tables (Eurostat, 2016) to allocate each observation to one of 402 administrative regions (AD, in German: *Stadt- und Landkreise*) (BBSR, 2017c). We then assigned each AD to one of 258 labor market regions (LMR, in German: *Arbeitsmarktregionen*) (Eckey, Kosfeld, & Türck, 2006). LMRs are the prevailing approach for delineating functional spatial entities in Germany. Like CBSAs in the U.S., LMRs are based on commuting patterns and are an attempt to form regions in which employees both live and work (Andersen, 2002; Cörvers, Hensen, & Bongaerts, 2009; OECD, 2002). However, unlike CBSAs, LMRs cover the entire surface of Germany. Finally, we assigned each AD to one of 96 planning regions (PR, in German: *Raumordnungsregionen)*. PRs are also functional spatial entities designed for large-scale spatial planning and for depicting broad regional development trends (BBSR, 2017d). We again excluded spatial entities with less than 50 observations. This eliminated 17 ADs (out of 402) and 7 LMRs (out of 258). The regional samples were highly representative of the actual number of inhabitants per region. Specifically, the correlation between regional sample size and regional population was .96 for the 385 AD, .97 for the 251 LMR and .96 for 96 the PR.

Parallel to Study 1, we tested measurement invariance for the medium spatial level (i.e. 251 LMR) and evaluated group mean reliabilities across regions. Out of the 2,510 tests (251 regions × 5 traits × 2 invariance conditions) for scalar and metric invariance only 15 (0.006%) exceeded the threshold of .01[10]. Table 5 reports the group mean reliabilities (ICC2) for each trait. Reflecting the smaller regional sample sizes at finer spatial levels, group mean

[10] This included ten violations of metric invariance for the traits agreeableness and emotional stability and five violations of scalar invariance for the trait agreeableness. Given that we ran 2,510 tests, 15 cases are a vanishingly small number (0.006% of all tests) and in no region both conditions were violated. Therefore, these results do not suggest any problematic issues, but rather represent the ordinary fluctuations of results one should expect when conducting such a high number of tests. Results are obtainable digitally from the authors upon request.

reliabilities were highest at the PR level (ranging from .64 to .91) and smallest at the AD level (ranging from .47 to .81). Overall, reflecting the generally smaller sample sizes in the German subsample, the group mean reliabilities for German regions were below those obtained for U.S. regions. To address the problem of increased sampling error in smaller regional samples, we based regional personality scores for all three spatial levels on *Best Linear Unbiased Predictors (BLUPs)* instead of raw means.

PESH indicators

Demographic indicators. To capture the demographic composition of the regions, regional estimates for gender, median age, and percentage of non-Germans (based on possession of German citizenship) were gathered. The variables form an average of the years 2010 to 2012 and were obtained via the Federal Institute for Building, Urban Affairs and Spatial Research (BBSR), which provides annual statistics based on updates of the last census for many indicators (BBSR, 2017b; Bayerisches Landesamt für Statistik, 2011).

Political indicators. Data addressing the regional political opinion were obtained from BBSR (2017b) and comprised the share of votes for the conservative party (CDU) in the parliamentary elections (*Bundestagswahl*) of 2009 and 2013.

Economic indicators. Regional prosperity is described by the average median income of the years 2010 to 2012 (BBSR, 2017b). To capture the creative and innovative potential of a regional economy (Griliches, 1990), the average number of patents per 1,000 employees between 2010 and 2012 was calculated based on data obtained from the PATSTAT database (European Patent Office, 2016). Information regarding the residency of the inventor was utilized to spatially aggregate the data.

Social indicators. To measure regional social stability, the share of married residents was included. As a differentiation between urban and rural communities/lifestyles, population density was included as a measure of urbanization (Statistische Ämter des Bundes und der

Länder, 2014). To capture the level of criminal activities, the average number of incidents of violent crime per 1,000 was obtained from the German Federal Criminal Office (BKA, 2015). All the previously described social indicators represent an average value of the years 2010 to 2012. Finally, given that a social capital index as in the U.S. was not available for the German case, we approximate the cultural and artistic capital in a region by the number of music bands per 1,000 residents. This was possible by utilizing information from the website www.bandliste.de (Rufeger, 2016), an open platform in which more than 10,000 German bands have registered in order to get booked for events[11].

Health indicators. Regional health levels were indicated by the life expectancy of a child born between 2011 and 2013 in the corresponding region (BBSR, 2017b).

Human capital. Regional human capital is represented by educational and occupational information. Education was depicted by the average share of employees holding a university degree in the period 2010 to 2012 (BBSR, 2017b). Occupational statistics were obtained directly from the census of 2011 (Bayerisches Landesamt für Statistik, 2011) and were based on the ISC0-08 classification (International Labour Organization, 2016). Here we differentiated between the share of employees in managerial & professional occupations, as well as trade & elementary occupations. Additionally, based on the demarcation of cultural and creative industries by the German Task Force for Cultural Statistics (Sönderman, 2009), the share of employees in creative industries was included (BBSR, 2017b).

Methods

Visualizing regional personality differences. To examine regional personality differences and their correlates in Germany, we applied the same analytical steps as in Study 1. In a first step, we used our bottom-up mapping approach (Brenner, 2017) to visualize the

[11] The authors manually downloaded all entries from this data base and, as most bands indicate the post code of their home base, it was possible to aggregate this information to a regional level. To the author's knowledge, this study is the first that exploits the underlying data base for scientific purposes.

spatial distribution of personality within Germany. Of note, in the U.S. case we used a distance decay function based on the bee-line distance between zip codes. However, to reflect the spatial range of human activity, bee distance might not be the most adequate measure. That is, some areas, although geographically near, might be difficult to access, while some more distal areas are well connected and can be accessed much quicker and easier. Importantly, the German case allows us to overcome this problem using a unique data set that provides the actual car travel time for the 11,165 × 11,165 pairs of German municipalities (Duschl, Schimke, Brenner, & Luxen, 2014).[12] The calculation of the score for each municipality then follows Formula 1, whereby r = 45 minutes in this case. Accordingly, participants nearby receive a weight of nearly one, participants with a distance of 45 minutes driving time receive a weight of 0.5, and participants further away than 60 minutes are considered with a weight of nearly zero.

Addressing the MAUP in the correlates of regional personality. We again ran OLS regressions to examine the correlates of regional personality scores across thee spatial levels (AD, LMR, PR) while partialling out gender, median age, educational attainment (share of people with university degrees), median income, and urbanity (population density). Again, all variables were *z*-standardized.

Managing spatial dependencies in the correlates of regional personality. We used Moran's I tests to check for spatial autocorrelation among the error terms of the previously run OLS regressions. To quantify the spatial interrelations between regions, we again used a row-standardized spatial-weight matrix based on Queen's adjacency (i.e., indicating whether two regions share a border or not).[13] Finally, to account for spatial dependencies, we again

[12] Our original data comprised zip code and not municipality information. We therefore used zip code information to assign each of the 110,029 individuals in our sample to one of the 11,165 German municipalities[12] (BBSR, 2017a). In case that a zip code spans across multiple municipalities, we assigned the zip code to the municipality it shows the greatest population overlap with.

[13] Although some regions had to be dropped due to insufficient sample sizes at the AD and LMR level, all regions featured at least on neighbor.

fitted a spatial lag model, that is, including spatially lagged values of the dependent variable. In accordance to Study 1, additional tests (see later) favored this spatial lag over a spatial error model in accounting for spatial dependencies.

Results and Discussion

Spatial distribution of personality within Germany. The first step of Study 2 was to evaluate the spatial distribution of personality traits across Germany. Using the same mapping approach as in Study 1, we were able to examine spatial patterns that are not diluted or constrained by administrative boundaries. The distribution of the Big Five across Germany can be seen in Figure 4. As was the case in Study 1, the spatial distributions of personality in Germany show a number of similar patterns across traits and also specific patterns for each trait. In many cases, distinct spatial clusters appear intuitive, as the referring area shares important commonalities. Furthermore, such distinct cluster spanned across administrative boundaries and also varied within them. A nice illustration of such a distinct cluster, is the case of Swabia in the Southwest. This cluster not only divides Baden-Wurttemberg almost perfectly along the historic borders of Swabia and Baden, but also spans into Bavaria, including the so-called Bavarian Swabians).

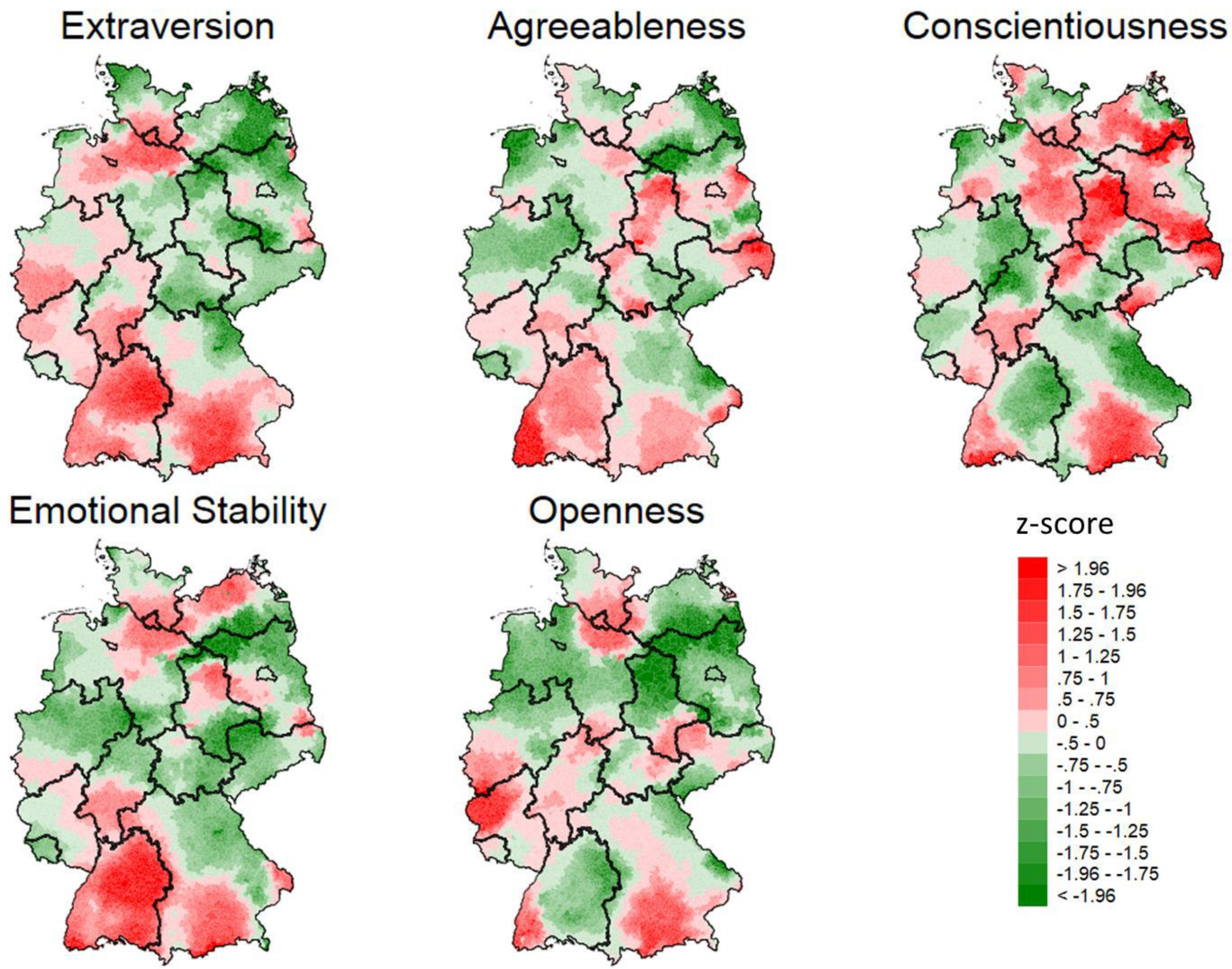

Figure 4. Mapping regional personality differences in Germany

Each trait showed a unique geographical pattern. For example, extraversion showed comparatively high levels in the Southwest of Germany (Swabia), the Munich area, the most western part of Germany, and the greater Hamburg/Bremen area in the North. Lower levels of extraversion appeared along the coastline of the North and Baltic Sea, large parts of East Germany, and along the Czech border. Comparatively high levels of agreeableness were observed in the Southwest of Germany, the greater Munich area, and parts of East Germany, whereas low levels of the trait were observed in the West/Northwest (Ruhr Area, East Westphalia, East Frisia), the very North East, and the Northern part of Bavaria (Franconia). High levels of conscientiousness emerged in many parts of East Germany and around agglomerations like Munich and Hamburg, and lower levels were found in broadly four different clusters in the Northwest (East Frisia), Central Germany, the Southwest (Swabia), and along the Czech border in the Southeast. For emotional stability, high average scores emerged in the Southwest, pockets of East Germany, and around the agglomeration areas of Hamburg, Munich and Frankfurt, whereas low average scores emerged in wide parts of western Germany (Ruhr area) and eastern Germany, as well as the Franconian part of Bavaria in the Southeast. Comparatively high levels of openness were found along the Luxembourgian and Belgian border in the West, Hesse in central Germany, in the very Southwest as well as around the agglomerations Munich, Hamburg and Leipzig. In contrast, low levels of openness were observed in Swabia, wide parts of East and North Germany. The map of openness nicely illustrates how the extensive belt of low openness in the North is broken up by the sphere of influence radiated by the agglomeration of Hamburg.

Taken together, the distributional patterns of personality presented here again highlight the merits of our mapping approach. In fact, the mapping approach revealed spatial clusters of personality that (a) are based on the actual spatial range of human activities and (b) would have been disguised by imposing prefixed administrative boundaries.

Correlates of regional personality across three spatial levels. In a second step, we evaluated the degree to which associations among regional personality and PESH indicators are prone to the MAUP. Table 6 reports the correlations between the personality and PESH indicators across three regional levels in Germany (385 AD, 251 LMR, 96 PR), when partialling out gender, median age, income, and urbanity.Overall, the observed relationships largely matched the results observed in Study 1, as well as previous findings in Great Britain (Rentfrow et al., 2015). Parallel to Study 1, the magnitude of effect sizes were again strongest at the highest level of aggregation, i.e. the level with the smaller number of spatial entities. A closer inspection of the PESH correlates across three spatial levels reveals in how far correlates from a specific spatial level generalize across other levels of spatial aggregation.

Table 6

Correlates of Regional Personality Scores across Three Spatial Levels in Germany.

Variable / Trait	Extraversion			Agreeableness			Conscientiousness			Emotional Stability			Openness		
	385 ADs	251 LMRs	96 PRs	385 ADs	251 LMRs	96 PRs	385 ADs	251 LMRs	96 PRs	385 ADs	251 LMRs	96 PRs	385 ADs	251 LMRs	96 PRs
Foreign born	**.32**	**.42**	.36	**.25**	**.45**	**.75**	.20	**.28**	**.73**	**.37**	**.44**	**.66**	-.07	-.05	.05
Conservat. Votes 2009	.03	.00	-.05	-.04	-.04	-.01	.07	.07	.05	-.08	-.11	-.10	-.02	-.06	.05
Conservat. Votes 2013	.12	.07	.03	.03	.02	.11	.12	.13	.08	.03	.00	.07	-.06	-.12	.00
Manager &Profess.	**.20**	**.23**	**.41**	**.44**	**.45**	**.63**	**.22**	**.19**	**.40**	**.30**	**.36**	**.52**	**.34**	**.45**	**.47**
Trade & Elementary	-.13	-.13	**-.24**	**-.34**	**-.35**	**-.40**	**-.24**	**-.18**	**-.40**	**-.27**	**-.28**	**-.44**	**-.31**	**-.44**	**-.42**
University degree	.11	**.16**	**.33**	**.41**	**.35**	**.52**	.12	.09	.23	**.17**	**.22**	**.32**	**.36**	**.41**	**.44**
Creatives	.05	**.17**	**.34**	**.23**	**.31**	**.42**	.09	**.17**	**.28**	**.14**	**.22**	**.27**	**.18**	**.33**	**.47**
Patents	.09	.14	**.27**	.05	.09	**.32**	.08	.08	**.28**	.05	.15	.23	.08	**.17**	.19
Life expectancy	**.29**	**.35**	**.44**	**.37**	**.47**	**.69**	**.24**	**.25**	**.37**	**.33**	**.43**	**.59**	**.14**	.15	**.28**
Married	.10	-.04	-.14	**-.25**	**-.27**	**-.46**	.11	.00	-.14	-.03	**-.18**	-.31	**-.42**	**-.47**	**-.57**
Violent Crimes	**-.19**	**-.18**	-.20	**-.16**	**-.14**	**-.25**	**-.19**	-.11	-.07	**-.16**	-.14	-.20	.01	-.04	-.15
Music Bands	.00	.06	.05	.06	.12	.21	**-.17**	-.11	-.10	-.08	.05	.09	**.21**	**.21**	**.24**

Note: Bold values indicate significance at the 5%-level. AD = Administrative district, LMR = Labor market region, PR = Planning region.

For extraversion, the strongest correlations at the AD level were positive associations with the share of foreign born and life expectancy. Both of these correlations also generalized to the LMR and the PR level (i.e., across all three spatial levels). Extraversion also correlated positively with managerial professions and negatively with violent crimes. Both of these relationships generalized to the LMR level, but not to the PR level. On the PR level, extraversion was positively associated with the share of people with university degrees, creative industries and patents, while being negatively associated with trade & elementary professions. Of these relationships, the associations for the share of people with university degrees and creative industries were also found at the LMR level.

Agreeableness was related to the share of foreign born, high human capital, creative industries, increased life expectancy, lower shares of married residents and lower rates of violent crimes at the AD level. Importantly, all these relationships generalized across all three spatial levels. At the PR level, agreeableness was additionally linked to an increased number of patents.

For conscientiousness, the strongest associations were a positive relationship with managerial professions and life expectancy as well as a negative relationship with trade & elementary professions. All these relationships generalized across all three spatial levels. At the AD level, conscientiousness was also negatively related to violent crimes and the presence of music bands. However, these relationships did not generalize to other spatial levels. At the LMR level conscientiousness was also positively correlated with the share of foreign born and creative industries, two relationships that were also found at the PR level. At the PR level, conscientiousness was additionally related to an increased number of patents.

Emotional stability was positively related to the share of foreign born, managerial professions the share of people with university degrees, creative industries, life expectancy, while being negatively related to trade & elementary professions and rates of violent crime. Apart from violent crime rates, all these relationships generalized across all three spatial levels. At the LMR level, emotional stability was also negatively linked to the share of married residents.

Openness was positively related to managerial professions, the share of people with university degrees and the presence of music bands. Apart from life expectancy (which was not significant at the LMR level), all these relationships generalized across all three spatial levels. At the LMR level, openness was also related to an increased number of patents.

Taken together, the results for Study 2 dovetail with those from the previous study demonstrating a considerable degree of robustness of regional personality scores and their correlates (i.e., not being artifacts of the MAUP). Across the three spatial levels, there was no significant change in sign. Associations that showed the strongest correlations at the AD level consistently generalized across the remaining levels. However, our results also highlight the importance of investigating relationships of aggregate personality scores across multiple levels. That is, some relationships were again only detectable for some levels of aggregation. Accordingly, studies investigating only one specific level risk reporting results that do not generalize to other spatial levels.

Managing spatial dependencies among error terms. In a third step, we assessed the extent to which the correlates of regional personality in Germany might be artifacts of spatial dependencies in the data. Again, we used Moran's I tests to assess the degree of clustering for the regional personality scores. Table 7 reports that for all five traits across all three levels there occurred highly significant spatial clustering (i.e., neighboring regions showing more similar scores) of small to medium magnitude. We then again checked how much of that spatial clustering remained among the residuals of our regression models (i.e., when accounting for the referring predictor and the complete set of control variables). Finally, we corrected for any remaining spatial autocorrelation by adding spatial lags. For reasons of parsimony, we only report the results for the finest spatial level (i.e, 385 ADs). The results for the LMR and PR level were conceptually similar and are reported in Online Supplement S6 and S7.

Table 7
Spatial Clustering of Big Five Personality Traits across three levels in Germany

	385 ADs		251 LMRs		96 PRs	
Trait	Moran's *I*	*p*	Moran's *I*	*p*	Moran's *I*	*p*
Extraversion	.15	.02	.18	.00	.12	.012
Agreeableness	.14	.00	.19	.00	.14	.003
Conscientiousness	.12	.00	.08	.00	.06	.098
Emotional Stability	.21	.00	.15	.01	.22	.000
Openness	.07	.00	.10	.00	.10	.026

Note: AD = Administrative district, LMR = Labor market region, PR = Planning region.

The second column for each trait in Table 8 reports the results of the Moran's I tests for the residuals of the OLS models. These tests revealed highly significant spatial autocorrelation of small to moderate magnitude for all five traits. Moran's I tests on the residuals of the spatial lag models (fourth column for each trait), reveal that including spatial lags successfully captured any existing spatial dependencies for extraversion, agreeableness, conscientiousness, and emotional stability. Significant autocorrelation among error terms only remained for openness. However, including spatial lags halved the degree of spatial autocorrelation for openness to a small magnitude that does not impose severe problems. Parallel to Study 1, we again repeated our analysis using a spatial error model instead of a spatial lag model. Again, as reported in Online Supplement S8, a spatial error model could not account for the spatial autocorrelation among error terms, hence corroborating our model choice.

Table 8

Correlates of AD-Level Personality Scores in Germany when accounting for Spatial Dependencies.

Variable / Trait	Extraversion				Agreeableness				Conscientiousness				Emotional Stability				Openness			
	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc
Foreign born	**.32**	**.06**	**.28**	-.01	**.25**	**.09**	**.20**	-.01	.20	**.08**	.17	.01	**.37**	**.12**	**.29**	-.02	-.07	**.10**	-.08	**.05**
Conservat. Votes 2009	.03	**.08**	.03	-.01	-.04	**.10**	-.03	-.01	.07	**.09**	.06	.01	-.08	**.14**	-.09	-.02	-.02	**.10**	-.01	**.05**
Conservat. Votes 2013	.12	**.08**	.11	-.01	.03	**.11**	.03	-.01	.12	**.09**	.10	.01	.03	**.14**	-.01	-.02	-.06	**.10**	-.05	**.05**
Manager &Profess.	**.20**	**.07**	**.19**	-.01	**.44**	**.06**	**.41**	-.01	**.22**	**.08**	**.20**	.01	**.30**	**.11**	**.25**	-.03	**.34**	**.09**	**.33**	**.06**
Trade & Elementary	-.13	**.08**	-.13	-.01	**-.34**	**.09**	**-.31**	.00	**-.24**	**.08**	**-.22**	.01	**-.27**	**.13**	**-.24**	-.02	**-.31**	**.08**	**-.31**	**.06**
University degree	.11	**.07**	.10	-.01	**.41**	.05	**.38**	-.02	.12	**.09**	.09	.01	**.17**	**.12**	**.13**	-.03	**.36**	**.09**	**.36**	**.05**
Creatives	.05	**.07**	.04	-.01	**.23**	**.08**	**.21**	-.01	.09	**.09**	.07	.01	**.14**	**.13**	**.12**	-.02	**.18**	**.09**	**.18**	**.05**
Patents	.09	**.07**	.06	-.01	.05	**.10**	.03	-.01	.08	**.08**	.06	.01	.05	**.14**	.01	-.02	.08	**.10**	.07	**.06**
Life expectancy	**.29**	**.06**	**.27**	-.01	**.37**	**.06**	**.35**	-.01	**.24**	**.09**	**.23**	.01	**.33**	**.09**	**.28**	-.03	**.14**	**.10**	**.13**	**.06**
Married	.10	**.08**	.08	-.01	**-.25**	**.08**	**-.20**	-.01	.11	**.10**	.13	.01	-.03	**.14**	-.01	-.02	**-.42**	**.07**	**-.42**	.02
Violent Crimes	**-.19**	**.07**	**-.17**	.00	**-.16**	**.11**	**-.16**	.00	**-.19**	**.09**	**-.19**	.01	**-.16**	**.13**	**-.12**	-.02	.01	**.10**	.02	**.05**
Music Bands	.00	**.08**	.00	-.01	.06	**.10**	.05	-.01	**-.17**	**.09**	**-.17**	.01	-.08	**.15**	-.10	-.02	**.21**	**.08**	**.21**	.03
Average change OLS to spatial model			9%				10%				5%				17%				2%	

Note: Bold values indicate significance at the 5%-level. AD = Administrative District. OLS mod. = OLS model, OLS. autoc. = OLS model autocorrelation, spat. Mod. = Spatial model, Spat. autoc. = Spatial model autocorrelation

Importantly, all correlations that were significant in the OLS models remained significant when including spatial lags. Overall, including spatial lags decreased the effect sizes from the OLS models. On average, significant effects shrank by 9% for extraversion, 10% for agreeableness, 5% for conscientiousness, 17% for emotional stability and 2% for openness. Accordingly, parts of the association between regional personality and PESH indicators can be explained by the level of the corresponding trait in neighboring regions. In line with the findings from Study 1, our findings suggest that associations between regional personality and PESH indicators are no artefact of spatial dependencies. However, the results from the German case again suggest that ignoring spatial dependencies can lead to a considerable overestimation of true effect sizes.

General Discussion

The central aim of the present work was to apply rigorous spatial methods to assess the generalizability, reliability and criterion validity of regional personality differences. To this end, we revisited established findings from the U.S. (Study 1) and extended them to the German context (Study 2). The results from our analyses converged with findings from previous studies, generalized across countries, and survived the scrutiny of rigorous spatial methods. The results from the current project have a number of empirical and theoretical implications.

To illustrate the spatial distribution of personality, we applied a mapping approach that allowed us to explore regional personality differences without aggregating the data to the regional level itself. Specifically, we performed a bottom-up approach in which regional clustering patterns of personality traits were not tied to a top-down raster of regions but were allowed to emerge freely from the data. Consequently, we avoided the issue of MAUP almost entirely, and the clustering patterns that emerged were not diluted by or an artefact of a predefined choice of spatial units. In other words, the clusters that emerged reflect the true boundaries of distinct psychological contexts. This is an important advancement to previous studies and provides much-needed evidence showing that systematic geographical differences in personality not only exist within nations, but also within and across the administrative areas (e.g., states) from which they are comprised.

In a next step, we systematically examined the correlates of regional personality scores across multiple levels of spatial aggregation while accounting for spatial dependencies. Importantly, we found that the correlates of regional personality scores largely generalized across spatial levels in terms of direction and significance. Additionally, we employed spatial lag models and showed that this specification successfully captured the existing spatial autocorrelation among error terms in our data. Including these spatial lags caused some effect sizes to shrink, however, with all correlations remaining intact, the achieved results corroborated the results of the conventional analyses. Limiting the probability of artefacts due to MAUP and spatial autocorrelation, the consistency across aggregation levels and model settings clearly indicate that the correlates of regional personality differences can be reliably studied. In other words, there appears to be a robust relationship between average personality scores and PESH indicators that is neither tied to the selection of spatial units nor an artefact of spatial dependencies. This finding generally supports previous research on regional personality differences that has only reported correlates for a single level of aggregation and that did not account for spatial dependencies. However, our findings also showed that the degree of clustering and spatial autocorrelation varied between personality traits and countries. An important task for future research will be to understand the nature of such clustering, with the aim of explaining why certain traits tend to be more highly clustered than others.

Additionally, our study highlights that regional variation in the Big Five personality traits are associated PESH indicators in similar ways across levels of analysis, language and the economic structure of the country. To facilitate comparisons of these associations, Table 9 summarizes the correlations between the personality and PESH indicators across the different spatial units for the U.S. and Germany. The patterns of results depicted in the table reveal several noteworthy findings. For example, examination of the correlations across different spatial units reveals a considerable degree of consistency: In 51 out of 80 (64%) instances, the direction of the correlations (or lack thereof) between the Big Five and PESH indicators was the same across all three spatial units of analysis within each country. And in 76 out of 80 (95%) instances, the direction of the correlations was the same across two consecutive spatial units of analysis within each country. Furthermore, in 22 out of 40 (55%) comparisons in the U.S. and in 29 out of 40 (73%) comparisons in Germany the direction of the correlations was the same across all three spatial units of analysis. And in 38 out of 40 (95%) comparisons in both the U.S. and also in Germany, the direction of the correlations was the same across two consecutive spatial units of analysis within each country. Taken together these patterns of findings address concerns related to the MAUP and indicate that the associations between aggregate personality traits and outcomes emerge consistently across multiple levels of spatial analysis.

Table 9

Summary of correlations between personality traits and PESH indicators across multiple levels of aggregation in the US and Germany.

	Extraversion						**Agreeableness**						**Conscientiousness**						**Emot. Stability**						**Openness**					
	USA			GER			USA			GER			USA			GER			USA			GER			USA			GER		
	CTY	CBSA	ST	AD	LMR	PR	CTY	CBSA	ST	AD	LMR	PR	CTY	CBSA	ST	AD	LMR	PR	CTY	CBSA	ST	AD	LMR	PR	CTY	CBSA	ST	AD	LMR	PR
Political																														
Conservative	+	0	0	0	0	0	+	0	+	0	0	0	+	+	0	0	0	0	-	-	0	0	0	0	-	-	-	0	0	0
Economic																														
Manag. Occ.	0	0	0	+	+	+	0	0	0	+	+	+	0	0	0	+	+	+	+	+	0	+	+	+	+	+	+	+	+	+
Trade Occ.	0	0	0	0	0	-	0	0	+	-	-	-	0	0	0	-	-	-	-	-	0	-	-	-	-	-	-	-	-	-
University	+	0	0	0	+	+	0	0	0	+	-	+	0	0	0	0	0	0	+	+	+	+	+	+	+	+	+	+	+	+
Social																														
Foreign born	-	-	0	+	+	0	-	0	-	+	+	+	-	-	-	0	+	+	+	+	0	+	+	+	+	+	+	0	0	0
Married	0	0	0	+	0	0	+	0	+	-	-	-	+	+	0	0	0	0	0	0	0	0	-	0	-	-	-	-	-	-
Violent Cri	-	-	0	-	-	0	0	0	0	-	0	0	0	0	0	-	0	0	0	0	0	-	0	0	+	+	0	0	0	0
Health																														
Life Expect.	+	+	0	+	+	+	+	+	0	+	+	+	0	0	0	+	+	+	+	+	+	+	+	+	+	+	0	+	+	+

Note. *CTY = County, CBSA = Core-based statistical area, ST = State, AD = Administrative district, LMR = Labor market region, PR = planning region. + = significant positive effect; - = significant negative effect; 0 = non-significant effect.*

Examination of the patterns of results for each of the Big Five personality traits in Table 9 also indicates that some traits yield more consistent results than others. Across all three spatial units in the U.S. and in Germany, the patterns of associations with PESH indicators were most consistent for openness and emotional stability. In contrast, agreeableness and extraversion showed comparatively less consistency across the different levels. The different patterns of for the Big Five traits suggest that openness and emotional stability maintain a robust and clear relationship with a range of PESH indicators from narrow up to broader spatial units. Taken together, our findings demonstrate that regional personality differences and their correlates are robust phenomena that can be reliably studied across multiple spatial units within and between countries.

Limitations and Future Directions

The present research shows that most of the correlations between regional personality scores and PESH outcomes are consistent across spatial levels. Furthermore, many of the regional correlates that were found in the U.S. were also found in Germany. However, the aggregate-level correlations do not consistently converge across countries and it is not always clear how to interpret aggregate-level relationships. When interpreting the correlates of regional personality, it is tempting to extrapolate from individual-level relationships to the aggregate level. In fact, such an approach can be a valuable extension to individual level research as the regional level provides a huge spectrum of indicators and enables the study of behaviors that have very low base rates (e.g., committing a violent crime). Furthermore, correlations at the aggregate level typically tend to yield large effects (Rushton, Brainerd, & Pressley, 1983) and hence might detect trends that would have been ignored otherwise (Rosnow, Rosenthal, & Rubin, 2000). On the other hand, interpreting aggregate level findings through the lens of existing individual level knowledge is subject to errors of the *ecological* and *individualistic fallacies.* Specifically, different levels of aggregation are logically independent, therefore, generalizations across multiple levels are not justified (Inglehart & Welzel, 2003; Robinson, 1950).

With respect to research on regional personality differences, some of the observed results from different studies show patterns of associations that are consistent between individual and aggregate levels of analysis, and sometimes they do not. For emotional stability and openness, the results reveal a remarkable consistency across different spatial unites and countries (McCann, 2011, 2013; Pesta et al. 2012; Rentfrow et al., 2008, 2009, 2015) that is in line with individual level findings (Ozer & Benet-Martınez, 2006; Roberts et al., 2007). However, the patterns of associations observed for extraversion, agreeableness, and conscientiousness appear less stable and fluctuate depending on the country and level of aggregation. Why do some traits show more consistency across levels than others?

One reason for the inconsistencies might be associated with the fact that regional PESH indicators are related to a wide variety of socio-demographic indicators (Bartholomae & Popescu, 2007; Fritsch & Stützer, 2007; Jansen & Brenner, 2016). Accordingly, relationships between regional personality scores and PESH indicators are subject to be contaminated by confounds. So far, research on regional personality differences (Rentfrow et al., 2008, 2015) has used rather basic sets of control variables that might only carve out genuine relationships for some personality dimensions but not others, or that might capture overlapping variance in some countries or spatial levels but not others. Consequently, it is possible that different confounds might disguise true relationships between some regional personality dimensions and PESH indicators.

Nonetheless, even if the results were not influenced by confounds and aggregate-level results were in line with individual level research, it would still be challenging to interpret the nature of the results without additional data. For illustrative purposes, consider the association between openness and regional prosperity. On one hand, it could be argued that openness drives regional prosperity. This idea is in line with research suggesting that regional prosperity is the result of the work of open-minded people living in the region (Florida, 2002). On the other hand, openness could also be a result of regional prosperity in the sense that having no financial worries allows people to be creative and appreciate artistic values. This idea is in line with research showing that personality traits can be subject to socialization effects and change in response to life events (Roberts, Wood, & Smith, 2005).

To avoid such pitfalls, it is necessary for future research to develop clear-cut theoretically driven hypotheses to explain the relationships between regional personality and PESH indicators, and to design tests of the hypotheses that allow for causal interpretations. One set of examples of research that tested causal explanations for regional personality differences can be found in Obschonka et al. (2015, 2016), which revealed that aggregate personality scores can predict regional start-up rates and economic resilience in the U.S. Furthermore, studies like Stuetzer et al., (2017) applied an instrumental variable design that allowed for additional tests of causality. The results from that work strongly suggests that regional personality scores are causal predictors of regional innovation and economic growth. Another example comes from work by Obschonka and colleagues (2018), who developed and tested the hypothesis that the closure of coalmines and factories during the Industrial Revolution led to unemployment and deprivation that persisted for generations in certain regions of Great Britain and predicts current levels of anxiety and depression. More research that uses such methods is clearly necessary to better understand how individual-level relationships between personality and behavior generalize to aggregate levels and to show how regional personality differences can be a valuable source of information for researchers across disciplines.

Conclusion

There is growing interest in geographical variation in psychological phenomena. With the availability of large geo-tagged psychological data (Adjerid & Kelley, 2018), this interest will almost certainly increase even more. So far, most psychological research concerned with geographical differences has relied on insights and methods that are suitable for psychological data but not spatial data. As a result, it was unclear to what extent geographical personality differences and their correlates were robust and reliable. Accordingly, it was timely and imperative to scrutinize our existing knowledge against the backdrop of spatial methods.

The present study forms an extension of previous investigations on regional personality differences. We used a new mapping approach that provides robust evidence that the U.S. and Germany are not homogeneous psychological entities but comprise different areas with distinct personality profiles. In both countries and across three spatial levels, regional personality differences proved to be robust predictors of a wide range of political, economic, social and health indicators. The majority of these relationships generalized across multiple levels of spatial aggregation and also remained when accounting for spatial dependencies in the underlying data. Considering that this is the first psychological study to apply rigorous spatial analysis techniques, our results generally support past research on regional personality differences and places this burgeoning area of research on a firmer foundation. Although our findings largely converge with previous findings, they also highlight that neglecting the peculiarities of spatial data can have serious effects on the outcome of a study. Accordingly, when working at the aggregate level, psychologists should be aware of the large array of analytical and methodological tools used that are designed to handle spatial data.

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Online Supplements

Online Supplement S1

Items and factor loadings for the Big Five personality traits in the U.S. subsample.

Item	Varimax-Rotated Principal Component				
	Extraversion	Emot. Stability	Conscient.	Openness	Agreeableness
Is talkative	**.76**	.08	-.02	.06	.04
Is reserved (r)	**.65**	-.08	-.08	-.05	-.03
Is full of energy	**.55**	-.17	.16	.18	.13
Generates a lot of enthusiasm	**.61**	-.06	.12	.27	.22
Tends to be quiet (r)	**.80**	-.07	-.01	-.05	-.05
Has an assertive personality	**.48**	-.09	.24	.20	-.20
Is sometimes shy, inhibited (r)	**.68**	-.25	.08	-.06	-.06
Is outgoing, sociable	**.78**	-.09	.06	.08	.16
Is depressed, blue	.29	**.49**	-.18	.10	-.17
Is relaxed, handles stress well (r)	-.05	**.69**	-.09	-.14	-.08
Can be tense	-.10	**.61**	.03	.07	-.23
Worries a lot	-.13	**.70**	-.04	.02	.01
Is emotionally stable, not easily upset (r)	-.04	**.64**	-.15	-.09	-.16
Can be moody	-.06	**.59**	-.11	.07	-.27
Remains calm in tense situations (r)	.01	**.56**	-.19	-.22	-.09
Gets nervous easily	-.26	**.60**	-.13	-.05	.07
Does a thorough job	.04	-.03	**.68**	.09	.07
Can be somewhat careless (r)	-.05	-.13	**.53**	-.13	.17
Is a reliable worker	.06	-.03	**.62**	.02	.18
Tends to be disorganized (r)	.01	-.10	**.59**	-.16	.04
Tends to be lazy (r)	.13	-.19	**.59**	-.04	.11
Perseveres until the task is finished	.04	-.07	**.64**	.13	.07
Does things efficiently	.06	-.10	**.64**	.12	.11
Makes plans and follows through with them	.14	-.09	**.55**	.05	.09
Is easily distracted (r)	-.07	-.29	**.51**	-.08	.03
Is original, comes up with new ideas	.18	-.13	.09	**.63**	-.02
Is curious about many different things	.11	-.03	.00	**.53**	.04
Is ingenious, a deep thinker	-.08	.03	.12	**.58**	-.04
Has an active imagination	.10	.05	-.10	**.63**	.02
Is inventive	.10	-.19	.10	**.64**	-.04
Values artistic, aesthetic experiences	-.02	.06	-.03	**.62**	.12
Prefers work that is routine (r)	.10	-.16	-.13	**.23**	-.08
Likes to reflect, play with ideas	.01	-.03	.03	**.64**	.05
Has few artistic interests (r)	.00	-.01	-.05	**.34**	.03
Is sophisticated in art, music, or literature	-.02	.03	-.07	**.57**	.04
Tends to find fault with others (r)	.02	-.27	.04	-.05	**.48**
Is helpful and unselfish with others	.08	-.05	.22	.13	**.52**
Starts quarrels with others (r)	-.16	-.23	.13	-.03	**.51**
Has a forgiving nature	.08	-.10	-.03	.11	**.56**
Is generally trusting	.14	-.07	.08	-.02	**.46**
Can be cold and aloof (r)	.28	-.14	.08	-.14	**.53**
Is considerate and kind to almost everyone	.05	-.02	.15	.12	**.69**
Is sometimes rude to others (r)	-.07	-.21	.16	-.03	**.61**
Likes to cooperate with others	.20	-.07	.19	.04	**.52**

Note: (r) = reverse keyed item.

Online Supplement S2

Correlates of CBSA-Level Personality Scores in the U.S. when accounting for Spatial Dependencies.

Variable / Trait	Extraversion				Agreeableness				Conscientiousness				Emotional Stability				Openness			
	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc
Foreign born	**-.14**	**.24**	**-.11**	-.01	-.03	**.26**	-.02	-.03	**-.08**	**.20**	**-.07**	-.01	**.19**	**.26**	**.13**	.01	**.32**	**.27**	**.23**	-.01
Republican 2008	.04	**.25**	.03	-.01	.05	**.27**	.03	-.03	**.13**	**.20**	**.10**	-.01	**-.07**	**.29**	**-.07**	.01	**-.25**	**.37**	**-.22**	.03
Republican 2012	.06	**.25**	.04	-.01	.05	**.27**	.02	-.03	**.13**	**.19**	**.09**	-.01	**-.07**	**.29**	**-.07**	.01	**-.27**	**.36**	**-.22**	.03
Manager &Profess.	-.06	**.25**	-.03	-.02	-.02	**.26**	-.01	-.03	-.06	**.20**	**-.07**	-.01	**.19**	**.30**	**.20**	.00	**.39**	**.37**	**.38**	.01
Trade & Elementary	.04	**.25**	.00	-.02	.04	**.26**	.02	-.03	.03	**.20**	.02	-.02	**-.25**	**.29**	**-.24**	.00	**-.44**	**.31**	**-.39**	-.01
University degree	.01	**.25**	.03	-.02	.03	**.26**	.03	-.03	-.03	**.20**	-.04	-.01	**.39**	**.28**	**.38**	-.01	**.54**	**.39**	**.51**	.02
Creatives	.01	**.25**	.02	-.02	-.01	**.26**	.00	-.03	.04	**.20**	.03	-.02	**.21**	**.26**	**.19**	.00	**.32**	**.28**	**.26**	-.02
Patents	**-.13**	**.24**	**-.11**	-.02	.01	**.26**	.00	-.03	-.04	**.20**	-.04	-.02	.01	**.29**	.02	.01	.07	**.34**	.05	.00
Life expectancy	**.25**	**.23**	**.20**	-.02	**.17**	**.26**	**.16**	-.04	.02	**.20**	.03	-.02	**.52**	**.25**	**.46**	.02	**.18**	**.36**	**.17**	.01
Married	**.11**	**.24**	.06	-.02	**.10**	**.26**	.05	-.03	**.24**	**.19**	**.20**	-.01	-.01	**.29**	-.04	.01	**-.39**	**.35**	**-.34**	.02
Violent Crimes	**-.10**	**.23**	**-.07**	-.02	.03	**.26**	.04	-.03	-.03	**.20**	-.02	-.02	.02	**.29**	.02	.01	**.10**	**.33**	**.06**	.00
Social Capital Index	**.12**	**.24**	**.10**	-.01	.05	**.26**	.04	-.03	.00	**.20**	-.01	-.02	**.08**	**.30**	**.08**	.01	**-.18**	**.30**	**-.09**	-.01
Average change OLS to spatial model			26%				29%				21%				10%				19%	

Note: Bold values indicate significance at the 5%-level. CBSA =Core-based statistical area. OLS mod. = OLS model, OLS. autoc. = OLS model autocorrelation, spat. Mod. = Spatial model, Spat. autoc. = Spatial model autocorrelation.

Online Supplement S3

Correlates of State-Level Personality Scores in the U.S. when accounting for Spatial Dependencies.

Variable / Trait	Extraversion				Agreeableness				Conscientiousness				Emotional Stability				Openness			
	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc
Foreign born	-.29	**.27**	-.19	-.05	-.32	**.15**	**-.34**	.02	-.19	**.26**	**-.22**	-.03	.12	**.21**	.02	-.04	**.76**	.09	**.69**	-.06
Republican 2008	.11	**.32**	.04	-.04	**.46**	**.21**	**.37**	.06	.26	**.24**	.09	-.01	-.17	**.22**	-.14	-.03	**-.67**	**.39**	**-.69**	.05
Republican 2012	.19	**.32**	.09	-.04	**.47**	**.21**	**.39**	.06	**.31**	**.24**	.15	.00	-.19	**.22**	-.15	-.03	**-.75**	**.36**	**-.73**	.03
Manager &Profess.	.00	**.32**	.17	-.03	-.50	.13	-.37	-.02	.13	**.22**	.20	-.06	**.47**	**.21**	.35	-.02	**.64**	**.26**	**.63**	-.03
Trade & Elementary	.29	**.25**	.12	-.06	**.53**	.13	**.43**	-.01	.01	**.23**	-.07	-.03	**-.37**	**.21**	-.24	-.01	**-.89**	**.14**	**-.87**	**-.07**
University degree	.02	**.32**	.16	-.04	-.47	**.15**	-.39	-.01	.14	**.21**	.18	-.06	**.64**	**.17**	**.50**	-.05	**.81**	**.31**	**.83**	-.02
Creatives	-.28	**.26**	-.19	-.05	**-.36**	**.15**	**-.31**	.02	-.11	**.23**	-.05	-.02	-.06	**.21**	-.09	-.05	**.50**	.12	**.44**	-.05
Patents	-.13	**.28**	-.02	-.05	.25	**.15**	**.27**	.01	.00	**.23**	.04	-.01	.09	**.22**	.12	-.03	.07	**.17**	.01	-.07
Life expectancy	.52	**.30**	.43	-.07	.40	.06	.29	-.06	.13	**.21**	.08	-.03	**.89**	**.16**	**.76**	-.04	.17	**.21**	.27	-.06
Married	.30	**.28**	.13	-.05	**.84**	**.25**	**.73**	.12	**.34**	**.22**	.17	-.01	.03	**.21**	.08	-.05	**-.88**	**.30**	**-.82**	-.02
Violent Crimes	-.21	**.32**	-.18	-.04	.02	.11	.05	-.04	.00	**.23**	.05	-.01	-.16	**.20**	-.16	-.05	.08	**.18**	.03	-.06
Social Capital Index	.19	**.29**	.16	-.06	**-.30**	**.22**	**-.27**	.06	-.09	**.26**	-.03	-.01	.04	**.21**	-.01	-.04	-.04	**.17**	.04	-.06
Average change OLS to spatial model			/				16%				51%				25%				7%	

Note: Bold values indicate significance at the 5%-level. OLS mod. = OLS model, OLS. autoc. = OLS model autocorrelation, spat. Mod. = Spatial model, Spat. autoc. = Spatial model autocorrelation.

Online Supplement S4

Spatial Autocorrelation when fitting a spatial error instead of a spatial-lag model in the U.S.

Variable / Trait	Extraversion			Agreeableness			Conscientiousness			Emotional Stability			Openness		
	2,547 counties	908 CBSAs	49 states	2,547 counties	908 CBSAs	49 states	2,547 counties	908 CBSAs	49 states	2,547 counties	908 CBSAs	49 states	2,547 counties	908 CBSAs	49 states
Foreign born	**.18**	**.24**	**.34**	**.24**	**.27**	**.67**	**.22**	**.20**	**.59**	**.27**	**.27**	**.58**	**.33**	**.29**	**.25**
Republican 2008	**.19**	**.26**	**.37**	**.23**	**.28**	**.46**	**.22**	**.20**	**.41**	**.27**	**.30**	**.68**	**.41**	**.42**	**.61**
Republican 2012	**.19**	**.26**	**.36**	**.23**	**.27**	**.46**	**.22**	**.19**	**.40**	**.27**	**.30**	**.67**	**.39**	**.40**	**.52**
Manager &Profess.	**.19**	**.26**	**.45**	**.24**	**.27**	**.55**	**.23**	**.21**	**.54**	**.27**	**.31**	**.63**	**.40**	**.39**	**.45**
Trade & Elementary	**.19**	**.26**	**.39**	**.24**	**.27**	**.46**	**.23**	**.20**	**.54**	**.26**	**.29**	**.62**	**.34**	**.32**	**.21**
University degree	**.19**	**.26**	**.43**	**.24**	**.27**	**.55**	**.23**	**.21**	**.52**	**.26**	**.29**	**.62**	**.38**	**.40**	**.48**
Creatives	**.19**	**.26**	**.32**	**.24**	**.27**	**.46**	**.23**	**.20**	**.47**	**.26**	**.27**	**.58**	**.34**	**.31**	**.26**
Patents	**.19**	**.25**	**.41**	**.24**	**.27**	**.68**	**.23**	**.20**	**.55**	**.28**	**.30**	**.61**	**.39**	**.36**	**.52**
Life expectancy	**.19**	**.24**	**.37**	**.24**	**.27**	**.61**	**.23**	**.20**	**.52**	**.23**	**.26**	**.62**	**.41**	**.39**	**.49**
Married	**.19**	**.25**	**.36**	**.22**	**.27**	**.35**	**.22**	**.20**	**.35**	**.28**	**.30**	**.60**	**.35**	**.37**	**.49**
Violent Crimes	**.18**	**.25**	**.36**	**.24**	**.27**	**.62**	**.23**	**.20**	**.56**	**.28**	**.30**	**.61**	**.38**	**.35**	**.46**
Social Capital Index	**.19**	**.25**	**.37**	**.24**	**.27**	**.61**	**.23**	**.20**	**.50**	**.26**	**.31**	**.59**	**.41**	**.35**	**.49**

Note: Bold values indicate significance at the 5%-level. CBSA = Core-based statistical area.

Online Supplement S5

Items and factor loadings for the Big Five traits in the German subsample.

Item	Varimax-Rotated Principal Component				
	Extraversion	Emot. Stability	Conscient.	Openness	Agreeableness
Is talkative	**.72**	.03	.02	.13	.10
Is reserved (r)	**.75**	-.11	-.02	-.01	.02
Is full of energy	**.50**	-.24	.30	.27	.01
Generates a lot of enthusiasm	**.58**	-.08	.08	.37	.04
Tends to be quiet (r)	**.81**	-.02	.01	.03	.01
Has an assertive personality	**.52**	-.17	.22	.20	-.31
Is sometimes shy, inhibited (r)	**.63**	-.29	.10	-.07	-.06
Is outgoing, sociable	**.76**	-.08	.02	.12	.11
Is depressed, blue	-.28	**.65**	-.13	.06	-.05
Is relaxed, handles stress well (r)	-.02	**.71**	-.05	-.11	.00
Can be tense	-.09	**.63**	-.02	.03	-.24
Worries a lot	-.18	**.62**	-.01	.09	.02
Is emotionally stable, not easily upset (r)	-.04	**.71**	-.10	-.07	-.09
Can be moody	-.07	**.59**	-.15	.08	-.28
Remains calm in tense situations (r)	.01	**.69**	-.15	-.16	-.02
Gets nervous easily	-.34	**.60**	-.17	-.02	.07
Does a thorough job	-.02	-.02	**.75**	.05	.03
Can be somewhat careless (r)	.00	-.10	**.67**	-.13	.07
Is a reliable worker	.01	-.04	**.73**	.08	.09
Tends to be disorganized (r)	.04	-.05	**.61**	-.14	.05
Tends to be lazy (r)	.18	-.13	**.62**	-.05	.11
Perseveres until the task is finished	-.02	-.11	**.62**	.13	-.03
Does things efficiently	.16	-.10	**.64**	.11	.02
Makes plans and follows through with them	.23	-.18	**.49**	.19	-.10
Is easily distracted (r)	.02	-.28	**.55**	-.03	.01
Is original, comes up with new ideas	.23	-.14	.07	**.64**	-.06
Is curious about many different things	.21	-.15	.12	**.51**	.07
Is ingenious, a deep thinker	-.14	.21	.04	**.44**	.01
Has an active imagination	.15	.01	-.02	**.66**	.01
Is inventive	.21	-.17	.09	**.67**	-.06
Values artistic, aesthetic experiences	-.01	.12	.00	**.64**	.13
Prefers work that is routine (r)	.13	-.15	-.14	**.18**	-.04
Likes to reflect, play with ideas	.01	-.03	-.06	**.59**	-.09
Has few artistic interests (r)	.01	.06	-.01	**.57**	.13
Is sophisticated in art, music, or literature	.02	.04	-.09	**.47**	.05
Tends to find fault with others (r)	-.12	-.23	.04	-.08	**.46**
Is helpful and unselfish with others	.07	.02	.17	.16	**.42**
Starts quarrels with others (r)	-.16	-.30	.14	-.04	**.45**
Has a forgiving nature	.09	-.21	-.06	.08	**.37**
Is generally trusting	.19	-.10	.05	.15	**.47**
Can be cold and aloof (r)	.19	-.07	.01	-.11	**.53**
Is considerate and kind to almost everyone	.02	.05	.18	.23	**.54**
Is sometimes rude to others (r)	.05	-.20	.08	-.07	**.62**
Likes to cooperate with others	.11	-.05	.08	.08	**.40**

Note: (r) = reverse keyed item.

Online Supplement S6

Correlates of LMR-Level Personality Scores in Germany when accounting for Spatial Dependencies.

Variable / Trait	Extraversion				Agreeableness				Conscientiousness				Emotional Stability				Openness			
	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc
Foreign born	**.42**	.05	**.39**	.01	**.45**	**.07**	**.38**	-.01	**.28**	.02			**.44**	**.06**	**.40**	.00	-.05	**.08**	-.05	.05
Conservat. Votes 2009	.00	**.06**	-.01	-.01	-.04	**.12**	-.04	-.01	.07	.03			-.11	**.09**	-.12	.00	-.06	**.08**	-.06	.05
Conservat. Votes 2013	.07	**.06**	.05	-.01	.02	**.12**	.00	-.01	.13	.03			.00	**.09**	-.02	-.01	-.12	**.09**	-.13	**.05**
Manager &Profess.	**.23**	**.06**	**.23**	-.01	**.45**	**.08**	**.41**	-.02	**.19**	.02			**.36**	**.06**	**.33**	-.02	**.45**	**.11**	**.46**	**.07**
Trade & Elementary	-.13	**.07**	-.14	.00	**-.35**	**.11**	**-.32**	.00	**-.18**	.03			**-.28**	**.08**	**-.26**	-.01	**-.44**	**.10**	**-.44**	**.07**
University degree	**.16**	**.06**	**.16**	-.01	**.35**	**.09**	**.32**	-.02	.09	.02			**.22**	**.06**	**.21**	-.02	**.41**	**.12**	**.42**	**.06**
Creatives	**.17**	**.06**	**.17**	-.01	**.31**	**.10**	**.28**	-.02	**.17**	.03			**.22**	**.07**	**.21**	-.01	**.33**	**.08**	**.33**	.03
Patents	.14	.05	.12	-.01	.09	**.11**	.04	-.01	.08	.02			.15	**.07**	.12	-.01	**.17**	**.07**	**.17**	.05
Life expectancy	**.35**	.04	**.33**	-.01	**.47**	**.06**	**.42**	-.01	**.25**	.01			**.43**	.03	**.41**	-.01	.15	**.08**	**.15**	.05
Married	-.04	**.06**	-.07	-.01	**-.27**	**.12**	**-.25**	-.01	.00	.03			**-.18**	**.08**	**-.18**	-.01	**-.47**	**.10**	**-.49**	.04
Violent Crimes	**-.18**	.04	**-.16**	-.01	**-.14**	**.11**	-.12	-.01	-.11	.03			-.14	**.07**	-.11	-.01	-.04	**.07**	-.03	.05
Music Bands	.06	**.06**	.06	-.01	.12	**.11**	.10	-.01	-.11	.03			.05	**.08**	.04	-.01	**.21**	**.08**	**.21**	.04
Average change OLS to spatial model			6%				12%								5%				2%	

Note: Bold values indicate significance at the 5%-level. LMR = Labor market region. OLS mod. = OLS model, OLS. autoc. = OLS model autocorrelation, spat. Mod. = Spatial model, Spat. autoc. = Spatial model autocorrelation.

Online Supplement S7

Correlates of PR-Level Personality Scores in Germany when accounting for Spatial Dependencies.

Variable / Trait	Extraversion				Agreeableness				Conscientiousness				Emotional Stability				Openness			
	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc	OLS mod.	OLS autoc.	Spat. mod.	Spat. autoc
Foreign born	.36	-.05			**.75**	**.09**	**.66**	.00	**.73**	.07			**.66**	**.08**	**.61**	-.01	.05	**.20**	.07	.06
Conservat. Votes 2009	-.05	-.04			-.01	**.15**	-.04	.01	.05	.06			-.10	**.11**	-.11	-.02	.05	**.18**	-.02	.06
Conservat. Votes 2013	.03	-.05			.11	**.13**	.05	.01	.08	.06			.07	**.10**	.03	-.02	.00	**.19**	-.07	.07
Manager &Profess.	**.41**	-.01			**.63**	.06	**.59**	-.03	**.40**	.05			**.52**	.03	**.49**	-.06	**.47**	**.16**	**.45**	.04
Trade & Elementary	**-.24**	-.01			**-.40**	**.13**	**-.38**	.01	**-.40**	.06			**-.44**	.07	**-.42**	-.03	**-.42**	**.18**	**-.40**	.06
University degree	**.33**	-.05			**.52**	.08	**.49**	-.03	.23	.06			**.32**	.08	**.31**	-.04	**.44**	**.18**	**.44**	.04
Creatives	**.34**	-.05			**.42**	**.10**	**.40**	-.02	**.28**	.05			**.27**	.08	**.26**	-.03	**.47**	**.12**	**.45**	.00
Patents	**.27**	-.05			**.32**	.08	.24	-.01	**.28**	.06			.23	**.09**	.19	-.02	.19	**.17**	.14	.06
Life expectancy	**.44**	-.03			**.69**	.04	**.65**	.00	**.37**	.07			**.59**	.06	**.56**	-.01	**.28**	**.16**	**.23**	.05
Married	-.14	-.04			**-.46**	**.15**	**-.47**	.01	-.14	.06			-.31	.07	-.29	-.03	**-.57**	**.20**	**-.60**	.04
Violent Crimes	-.20	-.07			**-.25**	**.11**	-.19	.01	-.07	.07			-.20	**.11**	-.18	.00	-.15	**.16**	-.09	.05
Music Bands	.05	-.05			.21	**.13**	.18	.01	-.10	.06			.09	**.10**	.09	-.02	**.24**	**.15**	**.22**	.04
Average change OLS to spatial model							10%								5%				7%	

Note: Bold values indicate significance at the 5%-level. PR = Planning region. OLS mod. = OLS model, OLS. autoc. = OLS model autocorrelation, spat. Mod. = Spatial model, Spat. autoc. = Spatial model autocorrelation.

Online Supplement S8

Spatial Autocorrelation when fitting a spatial error instead of a spatial-lag model in Germany.

Variable / Trait	Extraversion			Agreeableness			Conscientiousness			Emotional Stability			Openness		
	385 ADs	251 LMRs	96 PRs	385 ADs	251 LMRs	96 PRs	385 ADs	251 LMRs	96 PRs	385 ADs	251 LMRs	96 PRs	385 ADs	251 LMRs	96 PRs
Foreign born	**.06**	.05		**.09**	**.09**	**.10**	**.09**			**.12**	**.07**	**.09**	**.11**	**.09**	**.22**
Conservat. Votes 2009	**.08**	**.07**		**.11**	**.14**	**.15**	**.09**			**.15**	**.10**	**.12**	**.11**	**.10**	**.25**
Conservat. Votes 2013	**.08**	**.06**		**.11**	**.14**	**.15**	**.09**			**.15**	**.10**	**.11**	**.11**	**.10**	**.25**
Manager &Profess.	**.08**	**.07**		**.06**	**.09**	.08	**.08**			**.12**	**.06**	.05	**.10**	**.12**	**.18**
Trade & Elementary	**.09**	**.08**		**.09**	**.13**	**.14**	**.08**			**.13**	**.09**	**.09**	**.10**	**.12**	**.20**
University degree	**.08**	**.06**		**.05**	**.11**	**.09**	**.09**			**.13**	**.07**	**.09**	**.10**	**.13**	**.19**
Creatives	**.08**	**.07**		**.09**	**.11**	**.11**	**.09**			**.14**	**.08**	**.09**	**.10**	**.08**	**.14**
Patents	**.07**	**.05**		**.11**	**.14**	**.10**	**.09**			**.15**	**.08**	**.10**	**.11**	**.08**	**.20**
Life expectancy	**.06**	.04		**.07**	**.07**	.04	**.09**			**.10**	.04	.06	**.11**	**.09**	**.19**
Married	**.08**	**.07**		**.09**	**.14**	**.15**	**.10**			**.15**	**.09**	**.09**	**.07**	**.10**	**.21**
Violent Crimes	**.07**	.05		**.12**	**.13**	**.12**	**.10**			**.14**	**.08**	**.12**	**.11**	**.09**	**.20**
Music Bands	**.08**	**.06**		**.11**	**.13**	**.13**	**.09**			**.15**	**.09**	**.11**	**.09**	**.09**	**.18**

Note: Bold values indicate significance at the 5%-level. AD = Administrative District, LMR = Labor Market Region, PR = Planning Region.