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Personality and regional innovativeness - an empirical analysis of German patent data

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Abstract:

This paper contributes to the new literature on the role of personality for regional innovativeness by examining whether this role varies between different types of regions. Building on regionally aggregated levels of individual Big Five personality traits, we find that only extraversion has a positive effect on patenting in German regions. Its impact is particularly important in lagging regions. We interpret this result as an indication of the compensatory role of collaboration for the innovativeness of lagging regions characterized by low levels of (business) R&D, which demonstrates the need for place-sensitive policies that take into account different modes of innovation.

JEL: J24; O18; O30; R1
Keywords: Innovation, Big Five, Personality, Lagging regions

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1. Introduction

Personality traits are unequally distributed across geographic space, i.e., some personality patterns are more pronounced in certain regions than in others (Rentfrow et al., 2013; 2015). They are related to different political, socioeconomic, and demographic features of regions, suggesting that personality differences constitute an important element of regional heterogeneity (Obschonka et al., 2020). In this context, the Big Five model – originally developed as a general, cross-culturally validated taxonomy of *individual* personality traits – has also been used to conceptualize *regionally* aggregated personality patterns, which can be thought of as regional culture (McCrae, 2001; Hofstede & McCrae, 2004).

One area of research in which the Big-Five model has been used repeatedly is entrepreneurship. For example, Obschonka et al. (2015) show that the relationship between knowledge resources and the level of entrepreneurship in a region depends at least in part on "hidden" differences in entrepreneurial culture, as measured via the Big Five. Overall, there is a robust link between a region's local culture in terms of personality, attitudes, values, and norms – and regional entrepreneurship (also see Stuetzer et al., 2016; Audretsch et al., 2017; Obschonka et al., 2019a; Obschonka et al., 2020; Runst, 2013).

In contrast, the link between personality and the geography of innovation has only recently begun to attract researchers' attention. Lee (2017) uses the Big Five traits to study the "soft side of innovation", and to examine the corresponding relationship with patenting activity in travel-to-work areas in England and Wales. According to Lee's study and contrary to expectations, conscientiousness is the most important Big Five trait for regional innovativeness, which leads the author to conclude "a new focus – on hard work and organizational ability – is needed [to explain regional innovativeness]" (p. 106). This result is surprising since both entrepreneurship research (see Runst & Thomä 2022b) as well as innovation research (see Runst & Thomä, 2022a) point to other traits, such as openness, as an indicator of creativity, or extraversion, as a driver of communication, collaboration and knowledge exchange. The recently published regional study by Mewes et al. (2022) supports this assumption. Based on a broad database of psychological personality profiles (∼1.26 million people), this study, in contrast to Lee (2017), examines the influence of openness on regional innovation performance, not controlling for any other BF trait. Their results show that higher openness scores at the level of US metropolitan areas are related to patenting on breakthrough innovations but not to non-break-through-innovations.

We add to this recent literature by examining the relationship between aggregate values of the full Big Five inventory and regional patenting in German planning regions. Our contribution to the literature is twofold: First, we address the relationship between regional personality characteristics and regional innovativeness, thereby contributing to this novel strand of the literature (Lee, 2017; Mewes et al., 2022) but also exploring the role of the Big Five in cross-cultural comparisons (e.g., McCrae, 2001; Hofstede & McCrae, 2004; Rentfrow et al., 2015; Obschonka et al., 2019a). In particular, we investigate whether Lee's (2017) findings for England or Mewes et al.'s (2022) findings for the USA are supported in the case of Germany.

Second, we argue that the relationship between personality and regional innovativeness not only depends on the *type of innovation* (breakthrough vs. incremental, see Mewes et al., 2022) but also on the *type of region*. Patterns of learning and knowledge exchange can vary significantly between regions (Isaksen & Trippl, 2017; Parrilli et al., 2020). From a policy perspective, one particularly relevant distinction concerns leading and lagging regions. The recent study by Filippopoulos and Fotopoulos (2022) argues that the innovativeness of lagging regions differs from leadings regions, in that it is relatively more dependent on public R&D, softer innovation aspects – such tolerance and inclusion values – and, importantly, collaboration. Hervás-Oliver et al. (2021) suggest that European small and medium-sized enterprises (SMEs), which account for two thirds of overall employment, play a major role in regional innovation. In particular, they suggest that SME innovation in leading regions is driven by a combination of internal R&D, various kinds of external cooperation, and non-R&D inputs. In contrast, lagging regions rely fundamentally on external collaboration with other firms or other organizations. Both these and other articles (Wassman et al., 2016; Grillitsch & Nilsson, 2015) suggest that collaboration seems to be a key feature of successful innovation in lagging regions. We therefore argue that personality characteristics, and in particular such characteristics that relate to collaboration, are particularly important for the innovativeness of lagging regions.

2. Conceptual background

2.1. Taking personality to the regional level

The Big Five Inventory is the most established and validated model in psychology for measuring people's personality (Digman, 1990; John et al., 1991; 2008; McCrae & Costa, 2008). There are five independent traits which have been shown to remain mostly stable over an individual's life span (Cobb-Clark & Schurer, 2012;

Rantanen et al., 2007; Wortman et al., 2012). Extraversion is mainly associated with sociability but has also been linked to achievement orientation (Depue & Collins, 1999; Lukas et al., 2000; Nettle, 2005). Agreeableness is linked to a pleasant manner in social exchange but may also lead to conflict avoidance. Conscientiousness predisposes people toward being task-oriented, hardworking, and efficient. Emotional stability measures resilience in the face of set-backs, and openness indicates a willingness to experience novelty.

Aggregated personality data – usually generated by averaging the individual characteristics within a geographic area – have been widely used as an indicator of regional culture (Hofstede & McCrae, 2004; Rentfrow et al., 2008, 2013, 2015; Stuetzer et al., 2016; Obschonka et al., 2020; Mewes et al., 2022). While one can question the extent to which the abstract term "culture" can be conceptualized and measured in terms of aggregated Big Five traits, it seems plausible that that the increasing share of individuals with certain personality traits will affect the interactions of individuals within a region. As Rentfrow et al. (2008, p. 341) states, "the psychological and behavioral tendencies associated with those personality traits will tend to be more pervasive in that region than will tendencies associated with traits less common in that population."

There are a variety of potential and complex causes for cross-regional variation in personality patterns that are not yet fully understood by researchers. First, certain ways of life and everyday practices can have a long-term impact on people's attitudes (Alesina & Nunn, 2011; Inglehart, 2018) but also on psychological characteristics. As personality traits are not entirely heritable (Jang et al., 1996; Power & Pluess, 2015), this could happen through socialization (Hofstede & Hofstede, 2001), a process by which individuals acquire the traits that conform to the social standards of the dominant social group within a region. Alternatively, there could also be a (probably small) impact of individual personality traits on the likelihood of individual survival and procreation, affecting the composition of traits in the regional population. It is certainly plausible that some modes of subsistence may be more dependent on some personality traits than others. For example, farming most likely requires a higher degree of conscientiousness than hunting, because it can only be successfully practiced in the presence of constant, regular effort and long-term commitment (see MacDonald, 2008). Second, people with certain personality traits are often found in specific regions because migration is selective (Rentfrow et al., 2015). One may for example speculate, that migrants score higher on openness (and subsequently choose certain types of regions) than people who chose not to migrate. The exploration for such cross-regional trait variation lies beyond the scope of this paper. Instead, we build on the existing variation in regional personality patterns in order explore its effects on regional innovativeness.

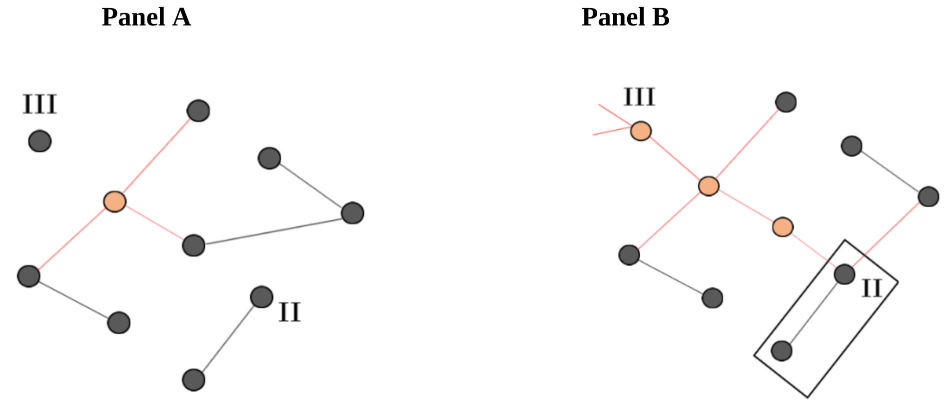
2.2. The Big Five and their expected impact on regional innovation

Firm-level literature provides evidence for a relationship between an individual's *openness* and *extraversion* score and their likelihood to become an entrepreneur (Zhao & Seibert, 2006; Nicolaou & Shane, 2010; Brandstätter, 2011; Caliendo et al., 2014; Runst & Thomä 2022b), as well as their likelihood to innovate once they are business owners (Runst & Thomä, 2022a; Marcati et al., 2008). One can therefore suspect a similar relationship between these two traits and innovation when moving from the individual (or firm) to the regional level.

Extraversion

Higher regional levels of extraversion – a trait that is primarily linked to sociability – are likely to be associated with higher levels of communication, collaboration and knowledge exchange at the regional level because it increases the number of social connections (or ties) between individuals, firms or other agents. Figure 1 depicts two different social networks (*A* and *B*) composed of such agents (indicated by the circles). An agent with high levels of extraversion (orange circle) is more likely to develop a connection with other agents within the network, and is therefore located closer to the network center. Certain portions of the overall network *A* remain unconnected to other actors, and knowledge that exists within these "social islands" is not accessible by all agents. According to the foundational paper of Social Network Analysis (Granovetter, 1973), agent *I* would critically benefit from access to agent *II*, who serves as a gateway to such island with all its knowledge and cooperation potential. Once agent *I* is represented as possessing a larger number of social ties (Panel *B*), the previously unconnected subnetwork is now accessible to agent *I*, and all information flows must pass through this node in order to reach all other agents. Within the context of regional innovation, agent *I* (as well as agent *III*) is therefore uniquely situated and should exhibit a higher likelihood to innovate, which in turn should spill over to all connected agents. Generally speaking, Panel *A* displays a situation with a lower share of extraverted individuals, which results in fewer overall connections. In contrast, Panel *B* displays a similar network with a higher share of extraverted individuals, resulting in a larger number of connections, thereby increasing an agent's likelihood to access knowledge that is available to other agents. According to another seminal paper by Coleman (1988), a well-connected and dense cluster of agents gives rise to reciprocity, trust, and shared information. Improved access to knowledge should positively affect the overall network capacity to produce innovations directly. The dense network structure should also indirectly support innovation by stimulating higher levels of cooperation.

Figure 1. Networks with low and high share of extraverted individuals



Openness

While a higher share of extraverted individuals should increase the number of network ties, a higher share of open individuals should affect the knowledge flows along those connections. Regions with higher aggregate levels of openness should therefore contain more entrepreneurs who monitor their external environment for new ideas and promising technologies (Sung & Choi, 2009; Zhao & Seibert, 2006). If agent *I* of Figure 1 receives knowledge from agent *II* which was hitherto unavailable to any other agent in his network (except *II*), an individual scoring higher in openness should be more willing to show interest in such news, whereas a less open individual should perhaps respond in a more skeptical manner, thereby hindering the further flow of information. It can also be argued that the degree of novelty will mediate the openness-knowledge-flow relationship. Almost by trait definition, the more novel the information the more likely it is that an individual scoring low in openness will reject it, which is in line with the findings by Mewes et. al (2022).

Conscientiousness

The regionally aggregated trait conscientiousness can theoretically affect innovation via its association with a commitment to a productivity enhancing work ethic. It could help to effectively and efficiently reap the innovation benefits of interactive learning at the regional level when organizational processes need to be adapted to make valuable knowledge from outside the region applicable within the regional innovation system (Miguélez & Moreno, 2015). Indeed, Lee (2017) finds evidence for a positive relationship between levels of conscientiousness and patenting activity in English and Welsh travel-to-work areas. This is somewhat surprising given the lack of individual-level evidence of an impact of this trait on innovation in the literature. Moreover, an efficiency orientation and strong work ethic could also be argued to enhance the exploitation of existing technologies and ways of doing business, rather that pursuing novel strategies, unless the production of new ideas is itself the result of dedication and grit, perhaps emerging through a trial and error process that requires a high level of perseverance. Overall, the theoretical and empirical considerations are ambivalent and we do not formulate a hypothesis with respect to the conscientiousness trait.

Agreeableness

A higher level of *agreeableness* among the people of a region may have a positive impact on the development of trust-based relationships, a shared understanding of regional identity and intensive cooperation, thus promoting innovation-enhancing interactive learning in the respective region (Lee, 2017). On the other hand, agreeable individuals seek to avoid situations of conflicts. By definition, innovation requires individuals to implement changes despite their environment's tendency to hold on to traditional routines, thereby precipitating some conflict of interests. The possible influence of agreeableness on regional innovation is thus by no means clear, which is why we do not formulate a hypothesis in this regard.

Neuroticism

Finally, *neuroticism (antonym: emotional stability)* measures an individual's susceptibility to stress and tension. Despite the lack of empirical evidence, it is therefore not unreasonable to argue that there is a negative relationship between the aggregate level of neuroticism and the innovativeness of a region.

2.3. Is personality more important for innovation in lagging regions?

We argue that the type of region constitutes an important mediating factor between psychological characteristics and regional innovativeness. More specifically, the impact of personality traits on innovation – in particular extraversion and openness – should be larger in lagging than in leading regions.

Regional innovation systems (RIS) consist of various components (Edquist, 1997), the various combinations of which creates a unique innovation environment. There are firms with their respective knowledge bases and know how, other organizations, such as universities, research institutes, and supporting infrastructures. Finally, governing capacity and formal as well as informal institutions also differ by region. Several recent papers reduce the heterogeneity of RIS by categorizing them into leading and lagging regions, describing their characteristics and exploring their respective determinants for innovation (Filippopoulos & Fotopoulos, 2022; Hervás-Oliver et al., 2021, Wassmann et al., 2016; Grillitsch & Nilsson, 2015). From this literature, collaboration emerges as a common element and key driver of innovation in lagging regions.

Filippopoulos and Fotopoulos (2022) apply exploratory fuzzy-set qualitative comparative analysis to Regional Innovation Scoreboard data. They suggest that lagging region are relatively more dependent on public R&D, softer innovation aspects – such tolerance and inclusion values – and firm collaboration than leading regions. Hervás-Oliver et al. (2021) focus on small and medium-sized enterprises (SMEs) as they that account for two thirds of overall employment in the European and play a major role in regional innovation. They also use Innovation Scoreboard data to perform regression analysis, which enables them whether determinants of SME innovation success differ by region type, defined by quantiles of innovation output. SME-innovation in leading regions is driven by a combination of private R&D and various kinds of external collaboration. In contrast, SMEs in lagging regions rely fundamentally on collaboration with other firms or external research organizations.

Similarly, Wassmann et al. (2016) analyze firm level data from low-tech micro firms in Bavaria. The authors identify a spatially diverse portfolio of cooperation partners as a determinant of innovation success. Most importantly, they provide evidence that the innovative capacity of lagging regions depends heavily on innovation-relevant knowledge exchange with cooperation partners outside the region. Similarly, Grillitsch and Nilsson (2015) argue and provide corresponding empirical evidence that firms in peripheral regions have reduced local access to knowledge, and must therefore collaborate at other geographical scales in order to "compensate for the lack of access to local knowledge spillovers". Their Swedish sample based on the Community Innovation Survey contains 2,261 innovative firms. The regression results show that successful innovators located in peripheral regions are more likely to engage in collaborative, multi-party innovation projects than firms in core-regions. Peripheral innovators are less likely to benefit from local knowledge spillovers and must therefore compensate for this deficiency by actively undertaking joint innovation projects.

Based on this new strand of the literature, collaboration with other firms and external research organizations emerges as a key driver of innovation in lagging (or peripheral) regions. We therefore hypothesize that personality traits that support collaboration are especially important for innovation in lagging regions. Most importantly, extraversion increases the connection between agents and increases enables or improves knowledge flows and cooperation as networks become more well-connected. While openness has also been argued to increase knowledge flows along existing network connections, a property that may well facilitate cooperation, this positive effect might be counteracted by the fact that lagging regions are not situated at the knowledge frontier. Instead of absorbing radically novel forms of knowledge, they may seek to access existing, locally embedded forms of knowledge, which have been implemented, tried and tested elsewhere even though they might be new to the firm itself. As the degree of novelty is not very high, the level of openness may well play a less important role. After all, the level of openness that is required to implement external innovations within the firm, which have been proven to work well for others, must not be quite so high.

3. Data and methods

3.1. Data

We use the German Socio-Economic Panel (GSOEP) and data by Peters and Matz (2022) for information on Big Five (BF) personality traits. As a well-established indicator for innovation, our dependent variable, we use patent application data which is available via the German Patent and Trade Mark Office (DPMA) and the European Patent Office (EPO)[1]. Control variables come from Eurostat, the Regional Innovation Scoreboard, the regional data archive of the Federal Statistical Office of Germany (Regionaldatenbank) as well as the INKAR database of the Federal Office for Building and Regional Planning (BBSR).

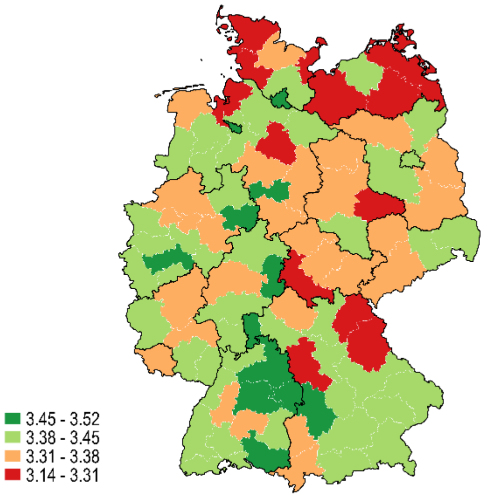
Individual-level Big Five survey items are available in the GSOEP[2] for the years 2005, 2009, 2013, and 2017.[3] In each year, 15 items were surveyed, three of which are associated with a specific Big Five trait. Small item scales such as the BFI-15 retain significant levels of reliability and validity compared with longer versions such as the BFI-44 (Rammstedt & John, 2007). There are about 11,500 individuals with complete Big Five traits in 2005, which increases to about 14,000 in the year 2017. Following Runst and Thomä (2022a) a factor analysis on this individual-level data yields a well-established five-factor solution (see Table A.1 in the Appendix), which is consistent with the results of previous studies (e.g. Hahn et al., 2012; Lang et al., 2011). The five factor scores (z-scores) are aggregated to the regional level of German planning regions (*Raumordnungsregionen*, ROR) by simple averaging. For the years without BF-trait information we use the values from the last available year, thus, for example, the BF-trait-values for 2006-2008 are the same as the one from 2005 etc. The value interpolation is justified by the largely stable nature of Big Five personality traits: they change only slowly and over longer lifetime spans if at all (Cobb-Clark & Schurer, 2012; Rantanen et al., 2007; Wortman et al., 2012). The mean number of individuals with BF-trait information per region is 142 but there are 84 region-year-observations with less than 40 survey responses, which we therefore exclude from the analysis. The final dataset is a panel with 1,332 observations from 2005 to 2018 within 96 planning regions (ROR). Planning regions are larger than NUTS3-regions but smaller than the 38 German NUTS2-regions.

While the GSOEP personality data permits us to construct a panel data set and apply region fixed effects, it might be objected that the number of trait observations in specific regions is somewhat low. We therefore also use a second source of regional Big Five scores based on the Big Five Project[4], a long-running international online survey. It is provided by Peters and Matz (2022), and has been used by a number of papers in psychology and economics (e.g. Obschonka et al., 2013; 2018). While this BF survey data contains a much larger number of observations, individual answers are not time coded. It was collected between 2002 and 2015 via a website (see Gosling et al., 2004). In addition, the Peters and Matz data was obtained via a BF-44 survey instead of the BF-15 in the GSOEP. By using this data set, we therefore lose the panel structure but gain measurement precision. Figure 2 displays the trait averages at the level of the planning regions. They generally conform to expectations. For example, peripheral and mountainous regions are less extraverted and open. They also correspond well to other choropleth maps of BF traits in Germany (see Obschonka et al., 2019b).

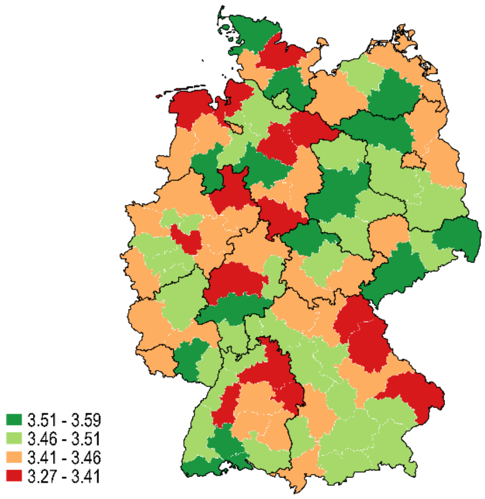
[1] We include EPO patent applications as an alternative to domestic patent applications to capture potentially different innovations due to factors underlying the decision where to apply (see e.g., Basberg (1983), Beneito et al. (2018) or Willoughby (2020)).
[2] German Socio-Economic Panel (GSOEP), data for years 1984-2019, GSOEP-Core v36, EU Edition, 2021, doi:10.5684/soep.core.v36eu.
[3] We do not include the 2019 GSOEP data on the Big Five because our regional data at the planning region level is only available for the years 2005 to 2018.
[4] https://www.thebigfiveproject.com/

Figure 2. Big Five personality traits at the regional level (see Peters and Matz, 2022)

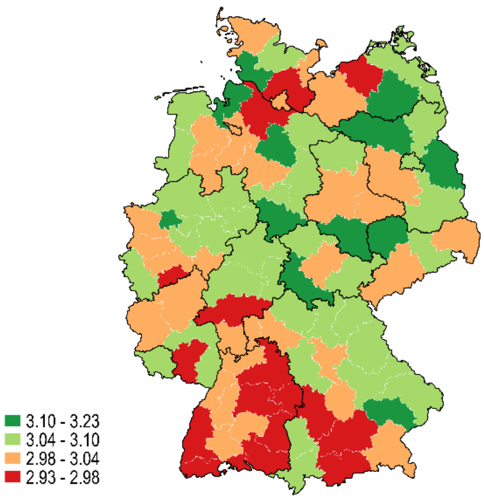
A. Extraversion



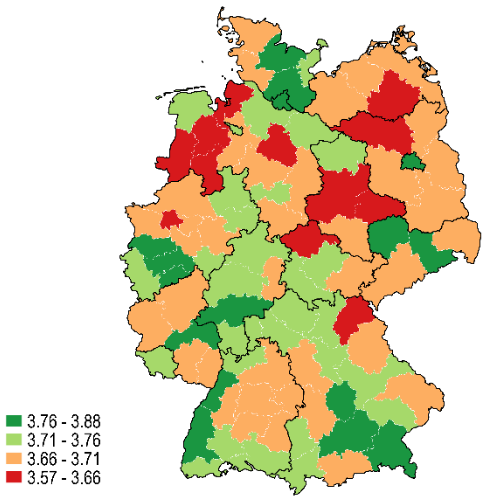
B. Conscientiousness



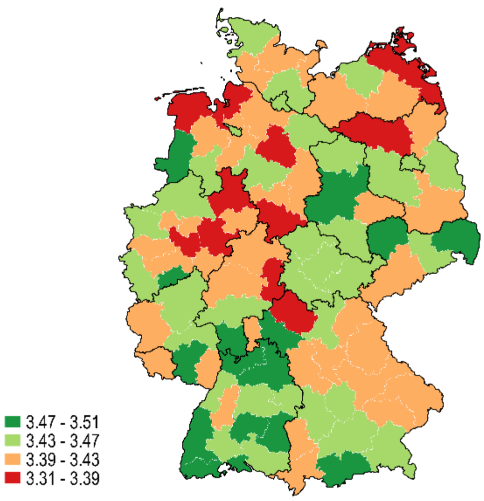
C. Neuroticism



D. Openness



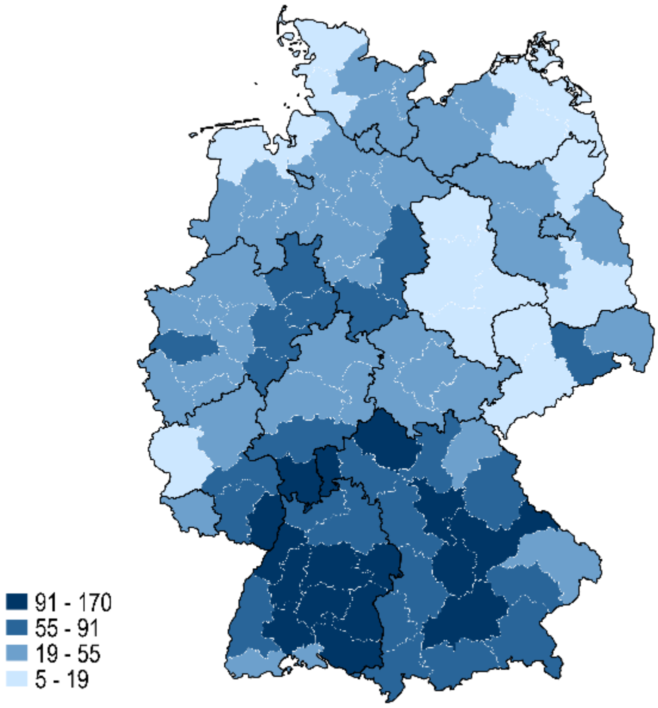
E. Agreeableness



The patent database of the DPMA (DPMAregister) can be publicly accessed through SQL queries[5]. Quarter-annual lists of all patent applications from its archive DEPATIS can be downloaded. We then use simple text recognition algorithms to extract postal codes of all participating inventors, applying fractional counting of patents and assigning each inventor *1/x* share of a patent, where *x* is the number of inventors per patent. We finally aggregate these numbers by planning regions. Similarly, the EPO database can be accessed via PATSTAT.[6] We use SQL queries to directly generate fractionally counted applications by year and NUTS3 region, which we subsequently aggregate to the level of planning regions.

Gross expenditure on R&D (GERD) by companies, governments and universities is provided by Eurostat. It is available on the NUTS2 level only. Thus, all planning regions within a NUTS2 region are assigned the same GERD value in a given year. Population data by region and year is taken from the Federal statistical office. The employment share in manufacturing as well as the number of students are provided by the INKAR regional data base[7]. Data on non-R&D expenditures has been obtained from the Regional Innovation scoreboard (RIS) of the European Commission.

Figure 3. DPMA-patent application per 100,000 inhabitants (by planning region, 2005-2018 average)



Source: DPMA

[5] https://register.dpma.de/
[6] https://www.epo.org/
[7] https://www.inkar.de/

Table 1. Descriptive statistics (planning regions, all years)

Variable	Source	Mean	Std. Dev.
Patents per 100,000 inhabitants (log)	DPMA	3.769	.75
Patents per 100,000 inhabitants (log)	EPO	2.544	.837
Big Five (Factor scores)			
Extraversion	GSOEP	.003	.097
Conscientiousness	GSOEP	.022	.115
Neuroticism	GSOEP	.003	.094
Openness	GSOEP	.001	.104
Agreeableness	GSOEP	.007	.107
Big Five (item averages)			
Extraversion	Peters and Matz (2022)	3.388	.063
Conscientiousness	Peters and Matz (2022)	3.464	.051
Neuroticism	Peters and Matz (2022)	3.037	.054
Openness	Peters and Matz (2022)	3.71	.051
Agreeableness	Peters and Matz (2022)	3.431	.037
Population	Federal Statistical office	885206	653347
Share of manufacturing employment	INKAR	.235	.082
Number of Students per 1,000 inhabitants	INKAR	25.95	17.216
Gross expenditure R&D business (log)	Eurostat	5.579	1.223
Gross expenditure R&D tertiary (log)	Eurostat	4.004	1.324
Gross expenditure R&D government (log)	Eurostat	4.553	.969
Non-R&D innovation expenditure (log)	RIS		
N		1,208	

Notes: GSOEP-survey-items are available in 2005, 2009, 2013, and 2017. They are based on an individual-level factor analysis – which are mostly bound between -2 and 2 standard deviations from the mean - and are subsequently aggregated to the regional level. Missing years are interpolated with lagged values. The regional BF trait variables provided by Peters and Matz (2022) are based on a large online survey (www.thebigfiveproject.com) where answers are recorded on a scale from 1 (strongly disagree) to 5 (strongly agree).

3.2. Methods

We perform fixed effects regression where the dependent variable is the logarithm of patents per 100,000 inhabitants. There are 94 planning regions for the years 2005-2018. Because of missing variables, there are 1,208 annual observations by region in our main specification. Standard errors are clustered at the regional level. We follow Lee (2017) and Mewes et al. (2022) in the choice of our control variables. For example, based on Griliches (1979), we use a knowledge production function to examine regional innovativeness, which assumes that innovation (as measured by patent applications) is a function of several factors. Accordingly, we include population, gross expenditure on R&D (GERD), the share of employees in the manufacturing sector, and the number of university students per 100,000 inhabitants as control variables to our regression model.[8]

Regional Innovation Typology

Finally, according to the hypotheses proposed above, we expect the effect of extraversion on innovation should be particularly strong in lagging regions. We therefore use a cluster analysis in order to divide the regions according to different innovation types. As an important contribution to the literature, this clustering procedure is based on the following innovation-related variables: 1. R&D expenditure by private actors, alongside that of the state and universities; 2. non-R&D related innovation expenditures, 3. the log of patents normalized by population, 4. Gross domestic product (GDP) as a general indicator for the structural strength or weakness of a region), and 5. the number of people with academic and vocational degrees. In conducting this cluster analysis, we can only use data for the years 2012 to 2018, as no values are available for earlier years. We seek to capture innovation that is not only related to R&D. Specifically, vocational training and non-R&D related innovation expenditure are likely associated with the doing-using-interacting mode of innovation (DUI, see Jensen et al., 2007; Isaksen & Trippl, 2017) which emphasizes firm-level innovation activities that are influenced by experience-based know-how embodied in people and shaped by informal processes of collaborative learning within and outside the firm.

[8] A correlation matrix can be found in the Appendix (Table A.2).

The complete use of our panel data set in a clustering procedure would have the disadvantage that the resulting clusters could be predominantly determined by time-effects. In an extreme case, if all innovation-related variables are increasing over time, the algorithm may yield one cluster of all planning regions in 2012, in which innovation-related variables are lower, and another cluster of all planning regions in 2018, in which innovation-related variables are higher. An alternative procedure would be to use mean values of all innovation-related variables over time, effectively removing the time component from the cluster analysis. Of course, such an approach cannot detect if regions move between innovation-types over time, which is quite probable in the course of regional development processes.

We therefore dismiss both approaches and perform separate cluster analyses for the years 2012, 2015, and 2018, filling in missing years with the last available information on the regional innovation type. We employ Ward's method of hierarchical clustering and a Euclidian distance measure to decide on the numbers of clusters to extract. The resulting cluster centroids serve as the starting values (seed points) for a subsequent k-means clustering procedure. In this way, the benefits of hierarchical clustering in determining the number of clusters are combined with the advantages of non-hierarchical cluster analysis in fine-tuning "the results by allowing the switching of cluster membership" (Hair et al., 1998, p. 498).

This ward/k-means cluster analysis approach yields three different groups of regions in terms of innovation (see Table 2). The third cluster is characterized by the highest value in all cluster variables except for the share of workers with vocational training. We label these the "leading regions" as this group is characterized by strong patenting activity, the largest R&D expenditures as well as the highest GDP per capita. It tends to be comprised of urban regions, as the population density is equal to 960 people per square kilometer. The opposite is true for the second cluster, as it has the lowest values for all cluster variables except vocational training, where it has the highest value. It is therefore referred to as the "lagging cluster" and it tends to be comprised of rural regions. It can be suspected that firm innovation in lagging regions is strongly influenced by the DUI mode of innovation. The "intermediate cluster" in column one combines high patenting output with a low share of academics, lower R&D expenditures, and relatively high degrees of vocational training and non-R&D innovation activity. Regions of this type are also mostly rural.

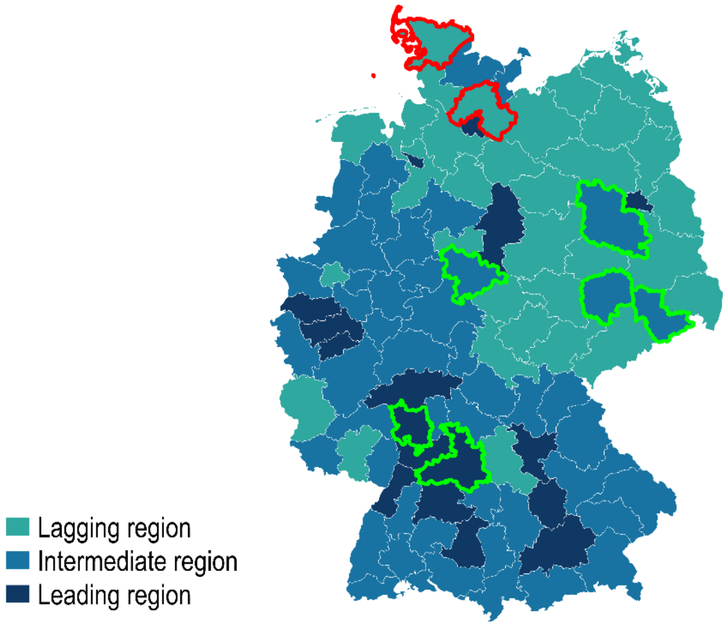
Figure 4 shows the change in regional cluster affiliation between 2012 and 2018. Most striking, almost the entire East of Germany consists of lagging regions, whereas leading regions are concentrated in the South. The six regions outlined in green, predominantly located in the East and the Southwest, show an upwards development from being a lagging region to intermediate regions, or from being considered an intermediate region to becoming a leading region. On the other hand, the two regions outlined in red in the North were considered intermediate regions in 2012 and are lagging regions by 2018.

Table 2. Cluster Analysis Results

	Cluster		
	I	II	III
Extraversion	-.002	-.000	-.010
Conscientiousness	.010	.056	-.044
Neuroticism	-.004	.030	-.018
Openness	-.007	-.014	.017
Agreeableness	.004	-.001	-.009
R&D business (log)	5.862	4.698	7.246
R&D tertiary (log)	4.581	4.206	5.885
R&D government (log)	3.642	3.936	5.797
Patents (log)	1.766	0.895	1.976
Population density	251.967	149.585	959.796
GDP per capita	34.889	26.501	48.161
VET training	65.735	69.450	56.806
Academics	10.885	10.752	18.304
Non-R&D innovation (log)	4.017	3.802	4.371
N in all years (2012-18)	335	230	107
2012	47	34	15
2015	49	32	15
2018	47	32	17
Label	intermediate	lagging	leading

Notes: Cluster variables are printed in bold. Resulting clusters are termed in Roman numerals. The number of planning regions sorted into clusters I-III in the separate years is shown in the bottom three rows.

Figure 4. Change in regional innovation type over time (2012-2018)



4. Results

4.1. Fixed effects regressions

The results of the fixed effects regressions – using GSOEP data as a source of BF traits – are shown in Table 3. Column (1) includes all BF personality traits, whereas in columns (2) to (6) the regression is run with each trait individually. Column (7) then includes all traits and several control variables. In these three sets of specifications, extraversion is the only personality trait that is consistently significant, exerting a positive effect on regional patenting levels. Once the control variables are included, the level of significance rises to 5%. Extraversion effect sizes are moderate to large: when extraversion increases by one unit or standard deviation in specification (1), patent applications approximately increase on average by 28% (or more precisely by ($e^\beta - 1$) ≈33%). Finally, for the purpose of robustness testing, column (8) restricts the sample to observations with more than 80 survey responses per region and year.

Besides extraversion, none of the other BF-traits exerts a significant and consistent effect across specifications (Table 3). The negative and significant effect of openness on patent applications in specifications 7 and 8 is perhaps most surprising, as at first glance it seems to show the opposite of what Mewes et al. (2022) found. As it is not consistent across specifications, it must be interpreted with caution however. It should also be noted, that the results of the latter study only show a positive relationship between openness and patenting on breakthrough innovations and neither on incremental innovations nor on innovations in general. Moreover, as patents are a tool for protecting intellectual property rights, one could argue that a culture of openness leads to a reduction in patent applications and is more likely to benefit the eponymous concept of open innovation (for a discussion on the relationship between patents and open innovation, see e.g. Da Silva, 2019; Hall, 2010; Lee et al., 2010; Pénin & Neicu, 2018). When the sample is restricted to at least 80 survey respondents per year per region (column 8), conscientiousness becomes significant, reflecting the main result of Lee (2017). However, significance does not hold across specifications either.

The coefficients of the control variables show to be insignificant except for population, which has a negative impact on patenting as was also found by Lee (2017), and R&D expenditure in the government sector, which positively influences regional innovativeness in terms of patenting.

Table 3. OLS regression results (level of planning regions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DPMA	*DPMA*	*DPMA*	*DPMA*	*DPMA*	*DPMA*	*DPMA*	*DPMA*
Years	2005-2018	2005-2018	2005-2018	2005-2018	2005-2018	2005-2018	2005-2018	2005-2018
Extraversion	0.283*	0.182*					0.204**	0.163*
Conscientiousness	-0.046		0.042				0.059	0.177**
Neuroticism	0.021			-0.040			0.099	0.087
Openness	-0.245				-0.108		-0.196**	-0.177*
Agreeableness	0.150					0.114	0.002	-0.058
Population							-0.000**	-0.000**
Manufacturing							-0.787	-0.996
Students							-0.002	-0.001
R&D business (log)							-0.025	-0.017
R&D government (log)							0.064**	0.086***
R&D tertiary (log)							0.028	0.003
Constant	3.747***	3.747***	3.747***	3.748***	3.749***	3.747***	5.365***	5.594***
N	1,245	1,245	1,245	1,245	1,245	1,245	1,208	900
R^2	0.379	0.370	0.366	0.366	0.368	0.368	0.536	0.592

Notes: DPMA refers to patent data from the German patent office. Column (8) restricts the sample to at least 80 survey respondents per year and planning region. Year and planning region fixed effects are included. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

In a second set of regression specifications, we use regional trait values based on the Big Five project[9] as described above. Again, the extraversion coefficient is the only one that is consistently and significantly different from zero. In columns (1) and (3), a one standard deviation increase in extraversion is associated with an increase in patenting that is similar to what has been found in Table 3, whereas it is half that in column (2). The conscientiousness coefficient is negative and significant in column (1) and (3), and insignificant in column (2), thereby not displaying a consistent effect across all specifications. Similarly, the three remaining personality traits neuroticism, openness, and agreeableness do not display coefficients that are different from zero except in column (3), where we see a negative agreeableness coefficient, albeit only at the 10% level.

Table 4. Regression with alternative Big Five variables (planning region level)

	(1) *Peters and Matz (2022)*	(2) *Peters and Matz (2022)*	(3) *Peters and Matz (2022)*
Years	2018	2018	2005-2018
Extraversion	5.249***	2.382**	5.088***
Conscientiousness	-2.716*	1.125	-4.161**
Neuroticism	-1.459	1.276	-2.096
Openness	0.654	0.632	-1.499
Agreeableness	1.000	-0.852	-9.564*
Population		-0.000**	-0.000**
Manufacturing		3.409***	2.227***
Students		0.001	-0.000
R&D business (log)		0.494***	0.162***
R&D government (log)		-0.019	0.058**
R&D tertiary (log)		-0.055	0.012
Constant	-5.809	-14.427	0.000
N	94	94	1,200
R^2	0.308	0.776	0.326

Notes: All specifications use survey data on Big Five traits available from Peters and Matz (2022) as well as DPMA patent data. Columns (1) and (2) are based on a cross-sectional regression in the year 2018. Column (3) uses a random effects model with year dummies. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01. In specification (2), a one unit increase in extraversion leads to an increase in the log of patents by about 2.4. In other words, a one standard deviation increase in extraversion (.097), increases the number of patents by 24%, which is similar to the results based on GSOEP BF variables.

4.2. Heterogeneous effects of the regional innovation type

Next, in order to elaborate whether personality is more important for the innovativeness of lagging regions (see Section 2), we perform our main regression specification (column (7) of Table 3) separately for each cluster sample (i.e. regional innovation types). We use GSOEP traits instead of trait data from Peters and Matz (2022) because the sample size in the cross-sectional data, once divided into three region types, is too small. Only the lagging cluster generates a positive and significant coefficient for extraversion (see Table 5 column two), which suggests that extraversion only matters in lagging regions and has a positive effect on patent applications there, but not in the intermediate-type regions nor the leading regions. Moreover, the coefficient is greater than in the baseline regression. This confirms our hypothesis stating that the link between personality and regional innovation exists especially in the less R&D-intensive environments of lagging regions.

[9] https://www.thebigfiveproject.com/

Table 5. Results from baseline (GSOEP) regression run on the three clusters separately

	(1) *DPMA* inter-mediate	(2) *DPMA* lagging	(3) *DPMA* lead-ing	(4) *Peters and Matz (2022)* inter-mediate	(5) *Peters and Matz (2022)* lagging	(6) *Peters and Matz (2022)* leading
Extraversion	0.123	0.334**	0.071	0.058	4.463***	-8.716
Conscientousness	-0.028	0.286	0.295	1.475	-0.409	12.208***
Neuroticism	0.126	0.120	0.212	0.148	0.019	-7.206
Openness	-0.094	-0.160	0.314	-0.280	-1.456	2.688
Agreeableness	0.141	-0.062	-0.292	0.409	-1.857	-18.510*
Population	0.000	-0.000	-0.000	0.000	0.000	0.000
Manufacturing	-0.237	-0.319	-4.436	-0.000	-0.000	0.000
Students	0.001	-0.001	-0.004	4.031***	3.213*	17.009***
R&D business (log)	-0.143**	0.095	0.069	0.004	-0.008	0.028*
R&D tertiary (log)	-0.049*	-0.022	0.330	0.380***	0.604***	0.280
R&D government (log)	0.047*	-0.270**	0.063	-0.042	-0.290	-0.475
Constant	4.271***	4.732***	2.575	0.014	0.065	0.904**
N	330	220	107	-5.035	-0.703	58.076
R^2	0.602	0.478	0.757	45	32	17

Notes: Based on specification (7) in Table 3 run separately on the three clusters which are indicated by Roman numerals I-III. Year and planning region fixed effects are included. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

4.3. Robustness

A first robustness check restricts the sample in Table 3 column (7) to the years 2005, 2009, 2013, and 2018, for which BF-GSOEP-survey data is available and not interpolated (see Table A.3 column (1) in the Appendix). Although the level of significance falls, extraversion is still significant at the 10% level. Second, we use data on European patent applications (EPO data) as an alternative dependent variable. In this case, results remain robust and yield a highly significant extraversion coefficient (Table A.3 column two).Third, one- and two-year lags of the R&D expenditure variables are used to account for a lag effect of R&D expenditure on innovation (Table A.4). When running the baseline specification at the fine-grained county level, for which the Big Five variables from Peters and Matz (2022) are available, the results also remain robust (Table A.5).

A further robustness check accounts for spatial autocorrelation by including spatial lags of the dependent variable, the error term and all independent variables (Table A.6 in the appendix). Similar to autocorrelation in time, when the value of some variable in location *i* depends on the values of that variable in neighboring locations *j*, this results in a biased estimation of the error variance, and regression results cannot be interpreted by means of inferential statistics (Anselin & Griffith, 1988). To account for this, weight matrices are employed in the regression where the weights are based on first-order queen contiguity or inverse distance. In the former weights matrix, elements are equal to one when region *i* and region *j* are neighbors, i.e. share a border or have a common vertex, and zero otherwise. Both weights matrices are normalized spectrally so that one is their greatest eigenvalue. In a second step, only the significant lags are kept in the regression (columns (2) and (4) of Table A.6). The results prove to be robust to spatial autocorrelation across all four specifications.

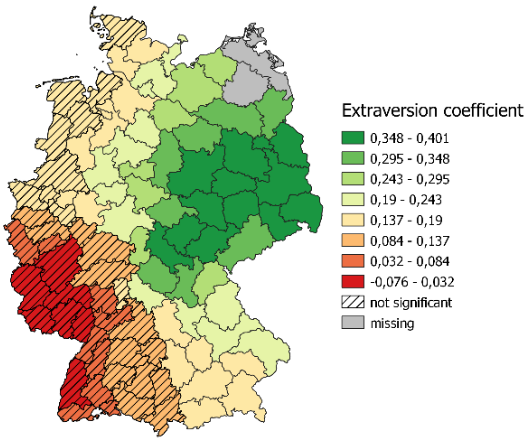
A third set of robustness checks relates to the heterogeneous effects found for the different regional innovation types. First, we exploit the fact that innovation activity and structural weakness of a region are related, although nonlinearly (Koschatzky & Kroll, 2019). Nevertheless, the regression results show to be robust when, instead of separating the samples by innovation-type regions, planning regions are simply divided into GDP terciles (Table A.*7*; see Filippopoulos & Fotopoulos 2022 for such an alternative GDP-based classification of lagging regions). We do the same for population density and the region type classification according to the Federal Office for Building and Regional Planning (BBSR) and also yield robust results.

We then explore spatial heterogeneity by applying a geographically weighted panel regression (GWPR) in which multiple regional samples are drawn to estimate regionally specific coefficients. The algorithm iterates through all regions *i*, generating a sample by including other regions *j* within a certain distance from *i*. In the regression, regional observations *j* are weighted more strongly if they are closer to *i* and are weighted less strongly if they are further away.[10] Figure 5 shows the results of the GWPR with an adaptive bandwidth of 62 regions, although results are similar when we use an optimal fixed bandwidth of 283 km. Extraversion has a positive and significant effect on patent applications in Central and Eastern Germany, its effect size becomes larger towards the East (see Figure 5, Panel A). Hardly any other region shows a significant effect. As the extraversion effect predominantely exists in lagging regions, which are mostly located in the East, the GWPR results constitute robustness of our hypothesis proposed in Section 2. Interestingly, the effects of the other four personality traits also exhibit certain geographical patterns, albeit with a smaller effect size. Conscientiousness positively affects patenting in the North and South, whereas it has a negative impact in some Western regions. The effect of neuroticism diagonally splits Germany into two parts where in the Northwest, the coefficients are positive and significant, while they are negative in the Southeast. Openness divides Germany horizontally and exhibits significant negative effects in the Northern half (see Figure 5, Panel D). While a similar cut can be seen for agreeableness, it only has a significant (positive) effect in few regions in the South. However, further research is needed on the geographic patterns for these four personality traits, as their lack of significance in our cluster analysis suggests that a region's innovation type is not the driving force behind regional heterogeneity in these cases.

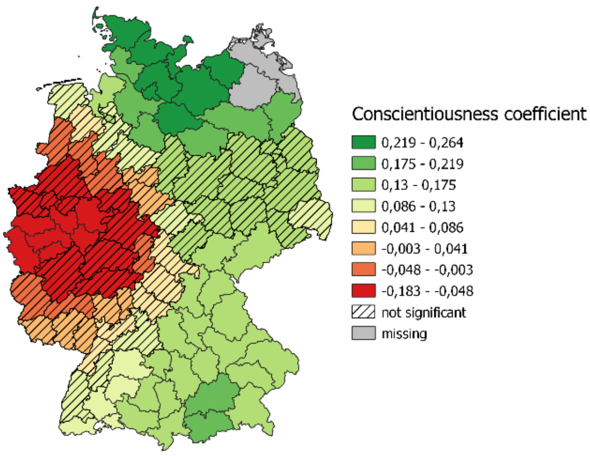
[10] We use the algorithm "GWPR.light" in the statistical software package R.

Figure 5. Geographically Weighted Panel Regression

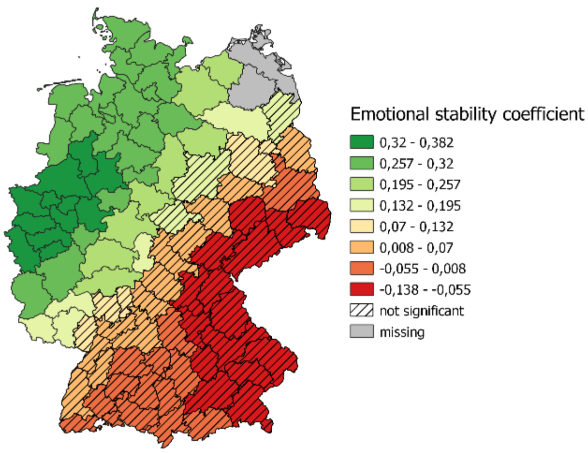
A. Extraversion



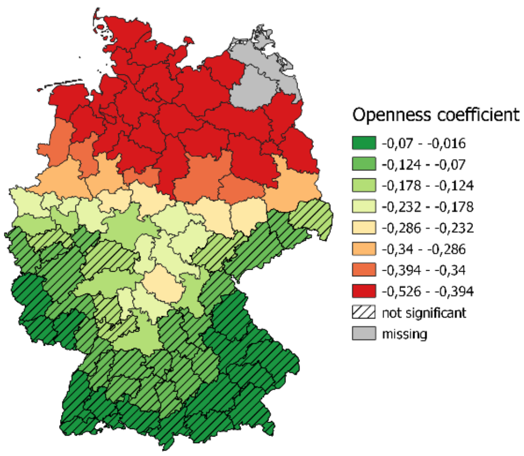
B. Conscientiousness



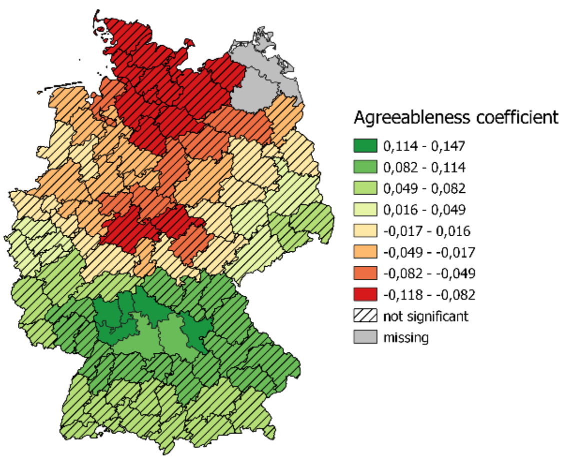
C. Neuroticism



D. Openness



E. Agreeableness



Notes: The package “GWPR.light” was used within the statistics software R. All specifications employ an adaptive bandwidth. The overall, non-locally constrained BF-coefficient is statistically significant at the 5% level in the case of extraversion (0.191) and openness (-0.18).

5. Conclusion

This paper examines the relationship between personality and regional innovativeness in a two-stage procedure by first looking at the general effect of aggregate Big Five scores on regional patenting levels and then addressing the variability in this effect with respect to the innovation type of a region. In contrast to the findings by Lee (2017) for the UK and Mewes et al. (2022) for the US, we find extraversion to foster innovation at the level of German planning regions. In this way, we contribute to the literature that uses the Big Five for cross-cultural or cross-national comparisons (e.g., McCrae, 2001; Hofstede & McCrae, 2004; Rentfrow et al., 2015; Obschonka et al., 2019a). We argue that extraversion increases the number of network ties within a region, thereby increasing communication, knowledge exchange and collaboration.

Moreover, we show that the relationship between personality and regional innovativeness depends on the innovation type of a region. We find that extraversion positively affects patenting in lagging regions, while it does not have a significant effect in leading or intermediate regions. The heterogeneous region-type effect supports recent studies showing that collaboration can serve as a compensatory mechanism for innovation in lagging regions (e.g. Filippopoulos & Fotopoulos, 2022; Hervás-Oliver et al., 2021). Thus, for lagging regions the aggregate regional level of extraversion may be a compensatory mechanism for their lack of business R&D. This means that an innovation policy approach for lagging regions that is place-sensitive and goes beyond a narrow R&D focus should consider the strong interactive component of innovation activities in these types of regions.

In addition, based on the cluster analysis results, one could suspect that firm innovation in lagging regions is more strongly related to the Doing-Using-Interacting Mode, which produces incremental, step-wise improvements rather than major break-throughs and is driven by collaboration and vocational training. Furthermore, it has been shown that SME innovation is associated with the personality of the firm owner (Runst & Thomä, 2022a), which corresponds well with the evidence for an extraversion-innovation relationship presented above. The relationship between lagging regions and the DUI-innovation mode should therefore be explored in further research.

One possible limitation of our study is that we examine the relationship between personality and regional innovativeness by using patenting as a measure of innovation (on the possible disadvantages of patents as an indicator of innovation, see e.g. Griliches, 1990). Future research could examine this relationship by measuring regional innovativeness more comprehensively, beyond STI-focused innovation indicators such as patents. Finally, the search for a suitable instrumental variable for extraversion would be a promising starting point for future research, in order to avoid potential endogeneity problems in the causal interpretation of our results.

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Appendix

Table A.1. Factor loadings of Big Five GSOEP-items (year 2017)

		extra-version	conscien-tuousness	open-ness	agree-ableness	neu-roticism
	I am someone who…	**1**	**2**	**4**	**5**	**3**
1	works thoroughly.	0.1873	**0.6594**	0.0532	0.1153	0.0293
2	is communicative, talkative.	**0.6631**	0.2529	0.1303	0.076	0.0093
3	is sometimes a little rough with others.	0.0526	-0.0664	0.0169	**-0.5477**	0.0804
4	is original, introduces new ideas.	0.3984	0.1982	**0.4374**	-0.1285	-0.0587
5	often worries.	-0.0542	0.0522	0.0061	0.0571	**0.5126**
6	can forgive.	0.1378	0.3211	0.0878	**0.267**	-0.0042
7	tends to be lazy.	-0.1269	**-0.3224**	0.1341	-0.32	0.0581
8	can go out of his way, is sociable.	**0.6506**	0.1884	0.202	0.0546	-0.1065
9	appreciates artistic experiences.	0.2149	0.1688	**0.4327**	0.2001	0.0604
10	gets nervous easily.	-0.0822	-0.0357	0.0556	-0.0537	**0.5872**
11	completes tasks effectively and efficiently.	0.2574	**0.5491**	0.1026	0.0625	-0.1176
12	is reserved.	**-0.4499**	0.2223	0.0798	0.0912	0.1952
13	is considerate and friendly with others.	0.1567	0.23	0.2122	**0.4885**	0.0334
14	has a vivid imagination, ideas.	0.2865	-0.031	**0.5268**	0.0685	0.0388
15	is relaxed, can handle stress well.	0.1277	0.2247	0.2875	0.1715	**-0.3809**

Notes: The factor analysis is performed on individual-level survey data (GSOEP).

Table A.2. Covariance matrix of regression variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Patents (log)	1.000											
(2) Extraversion	-0.056	1.000										
(3) Conscientiousness	-0.168	0.223	1.000									
(4) Neuroticism	-0.360	-0.321	0.118	1.000								
(5) Openness	-0.020	0.260	0.065	-0.046	1.000							
(6) Agreeableness	0.123	-0.020	0.368	-0.019	0.058	1.000						
(7) Population	0.195	-0.047	-0.152	0.015	0.056	0.002	1.000					
(8) Manufacturing	0.619	-0.126	0.009	-0.317	-0.011	0.233	-0.274	1.000				
(9) Students	0.158	-0.064	-0.324	-0.120	0.129	-0.060	0.345	-0.195	1.000			
(10) R&D business (log)	0.719	-0.121	-0.242	-0.307	0.044	0.017	0.658	0.254	0.352	1.000		
(11) R&D government (log)	0.103	-0.109	-0.065	0.112	0.019	0.068	0.585	-0.328	0.304	0.517	1.000	
(12) R&D tertiary (log)	0.322	-0.091	-0.117	-0.018	0.103	0.164	0.745	-0.118	0.504	0.727	0.783	1.000

Notes: Covariance matrix of variables used in the main regression specification. To account for the panel structure of the data, the correlations are only portrayed for the year 2018. Further, only regions with more than 40 survey responses are included.

Table A.3. Regressions with limited years or EPO patent data

	(1) *DPMA*	(2) *EPO*
Years	2005, 2009, 2013, 2017	2005-2018
Extraversion	0.181*	0.320**
Conscientiousness	0.057	0.061
Neuroticism	-0.037	0.131
Openness	-0.116	-0.340**
Agreeableness	-0.023	-0.139
Population	-0.000**	-0.000***
Manufacturing	0.102	3.058*
Students	-0.002	0.002
R&D business (log)	-0.063	0.055
R&D government (log)	0.075*	0.114***
R&D tertiary (log)	0.047	-0.015
Constant	5.213***	2.647***
N	432	1,197
R^2	0.525	0.234

Notes: DPMA refers to patent data from the German patent office, EPO stands for European Patent Office. Year and planning region fixed effects are included. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

Table A.4. Regression with lagged R&D expenditure

	(1) *DPMA*	(2) *DPMA*
Years	2006-2018	2007-2018
Extraversion	0.206**	0.186**
Conscientiousness	0.043	0.028
Neuroticism	0.142*	0.130*
Openness	-0.164*	-0.133
Agreeableness	0.022	0.025
Population	-0.000**	-0.000**
Manufacturing	-1.632	-1.730
Students	-0.002	-0.001
1-yr-lag R&D business (log)	-0.063	
1-yr-lag R&D government (log)	0.062***	
1-yr-lag R&D tertiary (log)	0.045*	
2-yr-lag R&D business (log)		-0.086
2-yr-lag R&D government (log)		0.053**
2-yr-lag R&D tertiary (log)		0.069***
Constant	5.869***	5.880***
N	1120	1031
R^2	0.556	0.569

Notes: Year and planning region fixed effects are included. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

Table A.5. County level regression

	(1) *Peters and Matz (2022)*	(2) *Peters and Matz (2022)*
Extraversion	1.866***	1.673***
Conscientiousness	-0.931**	-0.737*
Neuroticism	-1.077**	-0.894*
Openness	0.790	1.373***
Agreeableness	1.022*	1.144**
Population		-0.000***
Manufacturing		2.246***
Students		0.000
Research-intensive sectors		-0.000
Constant	-2.488	-6.301*
N	5560	3978
R^2		

Notes: Both specifications are at the county level and use survey data on Big Five traits available from Peters and Matz (2022) as well as DPMA patent data. Based on a random effects model with year dummies. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

Table A.6. Results from spatial regression

	(1) *Contiguity*	(2) *Contiguity*	(3) *Distance*	(4) *Distance*
Extraversion	0.118**	0.119**	0.159***	0.166***
Conscientousness	0.078	0.074	0.049	0.061
Neuroticism	0.111**	0.107*	0.117**	0.115**
Openness	-0.168***	-0.172***	-0.159***	-0.158***
Agreeableness	0.019	0.022	0.026	0.028
Population	-0.000***	-0.000***	-0.000***	-0.000***
Manufacturing	-0.821*	-0.812*	-0.992**	-1.115**
Students	-0.003***	-0.003***	-0.003**	-0.003**
R&D business (log)	0.005	0.001	0.010	0.006
R&D tertiary (log)	0.010	0.013	0.016	0.019
R&D government (log)	0.019	0.018	0.031	0.031
Spatial Lags				
Population	-0.000*	-0.000***	-0.000***	-0.000***
Manufacturing	-1.112		-5.727	
Students	-0.002		-0.015*	-0.007
R&D business (log)	-0.026		-0.445*	-0.322
R&D tertiary (log)	0.026		0.056	
R&D government (log)	0.105*	0.129***	0.437*	0.472**
Patents (log)	0.092		0.018	
Error term	0.184*	0.272***	0.057	
Constant	0.127***	0.127***	0.129***	0.129***
N	1316	1316	1316	1316

Notes: Contiguity and Distance stand for weights matrices based on contiguity or inverse distance. All specifications include year and planning region fixed effects. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.

Table A.7. Results from baseline regression run separately on the GDP terciles, population density terciles and BBSR regions

	(1) *DPMA* Low GDP	(2) *DPMA* Medium GDP	(3) *DPMA* High GDP	(4) *DPMA* Low PD	(5) *DPMA* Medium PD	(6) *DPMA* High PD	(7) *DPMA* Rural region	(8) *DPMA* Regions with first signs of ur-banization	(9) *DPMA* Urban region
Extraversion	0.359**	0.046	0.043	0.288*	0.069	0.010	0.384**	0.081	0.228
Conscientiousness	0.034	0.100	0.101	-0.079	0.032	0.156	-0.176	0.191*	0.025
Neuroticism	0.106	0.160	-0.026	0.274	-0.071	0.065	0.200	-0.003	0.178
Openness	-0.516***	-0.181	0.159	-0.143	-0.248**	-0.100	-0.156	-0.230	-0.133
Agreeableness	0.046	-0.092	-0.016	0.127	-0.123	-0.005	0.161	-0.091	-0.065
Population	-0.000**	0.000	-0.000**	-0.000***	-0.000	-0.000***	-0.000***	-0.000	-0.000***
Manufacturing	-1.182	0.257	-2.135	-1.515	-1.218	1.104	-1.542	0.685	1.977*
Students	-0.006	0.003	-0.002	-0.005	-0.010**	0.002	-0.011***	-0.000	0.001
R&D business (log)	-0.047	0.087	-0.106	-0.108	0.072	-0.070	-0.131	0.017	0.047
R&D government (log)	0.029	0.065*	-0.042	-0.053	0.026	-0.021	-0.051	0.041	-0.083**
R&D tertiary (log)	0.067	0.081***	0.013	-0.050	0.049	0.038	0.023	0.123**	-0.029
Constant	4.522***	2.465***	6.915***	6.007***	4.396***	5.332***	6.245***	3.444***	5.149***
Observations	414	405	389	362	421	425	427	449	332
R^2	0.574	0.584	0.586	0.617	0.618	0.711	0.624	0.581	0.766

Notes: Based on specification (7) in Table 3 run separately on GDP, population density (PD) and BSSR region type terciles. Year and planning region fixed effects are included. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at 0.10, 0.05 and 0.01.