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Personality and regional innovativeness: An empirical analysis of German patent data[☆]

Leonie Reher[a,b,*], Petrik Runst[b,c], Jörg Thomä[b]

[a] Chair of Economic Policy and SME Research, Georg-August-Universität Göttingen, Platz der Göttinger Sieben 3, 37073 Göttingen, Germany
[b] Institute for Small Business Economics at the Georg-August-University Göttingen, Heinrich-Düker-Weg 6, 37073 Göttingen, Germany
[c] Thuenen Institute of Rural Economics, Bundesallee 64, 38116 Braunschweig, Germany

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ABSTRACT

This paper brings together the literature on regional variability in innovation activity with studies on the role of personality for regional innovativeness. Building on regionally aggregated levels of individual Big Five personality traits obtained from the German Socio-Economic Panel and the Big Five Project, we find that only extraversion has a positive effect on patenting in German regions. This effect is particularly strong in the case of lagging regions. We interpret this finding as an indication of the compensatory role of collaboration for the innovativeness of lagging regions characterized by low levels of business research and development (R&D) and a dominance of small and medium-sized enterprises (SMEs), which demonstrates the need for place-sensitive policies that consider different modes of innovation and emphasize interregional and intraregional learning.

1. Introduction

Personality traits are unequally distributed across geographic space, i.e. some personality patterns are more pronounced in certain regions than others (Rentfrow et al., 2013, 2015). They are related to different political, socio-economic, 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 and McCrae, 2004).

One area of research in which this regional perspective on the Big Five model has been repeatedly applied is entrepreneurship. For example, Tavassoli et al. (2021) show that the quality of entrepreneurship in US cities is affected by local personality characteristics measured by the Big Five. Overall, there is a robust link between a region's local culture – measured in terms of personality, attitudes, values, and norms – and regional entrepreneurship (Stuetzer et al., 2016; Audretsch et al., 2017; Obschonka et al., 2015; Obschonka et al., 2019b; Obschonka et al., 2020; Runst, 2013). By contrast, the link between the Big Five 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 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 that "a new focus – on hard work and organizational ability – is needed [to explain regional innovativeness]" (p. 106). This result is noteworthy since both entrepreneurship research (see Runst and Thomä, 2023) as well as innovation research (see Runst and Thomä, 2022) 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 the latter findings. Based on a broad database of psychological personality profiles (~1.26 million people), their study examines the influence of openness on regional innovation performance, not controlling for any other Big Five trait. Their results show that higher openness scores at the level of US metropolitan areas

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* Corresponding author at: Chair of Economic Policy and SME Research, Georg-August-Universität Göttingen, Platz der Göttinger Sieben 3, 37073 Göttingen, Germany.

E-mail addresses: leonie.reher@uni-goettingen.de (L. Reher), petrik.runst@thuenen.de (P. Runst), Joerg.Thomae@wiwi.uni-goettingen.de (J. Thomä).

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are related to patenting of breakthrough innovations but not incremental innovations.

We add to this literature by examining the relationship between aggregate values of the full Big Five Inventory and regional patenting in German planning regions. We argue that the relationship between aggregated Big Five scores and regional innovativeness not only depends on the *type of innovation* (breakthrough vs. incremental, see Mewes et al., 2022) but also the *type of region*, given that patterns of learning and knowledge exchange can significantly vary between regions (Isaksen and Trippl, 2017; Parrilli et al., 2020). From a policy perspective, one particularly relevant distinction concerns leading and lagging regions. For example, the recent study by Filippopoulos and Fotopoulos (2022) argues that the innovativeness of lagging regions differs from leading regions in the sense that it is relatively more dependent on public research and development (R&D), softer innovation aspects such as tolerance and inclusion values, and – most importantly – collaboration. Similarly, regarding small and medium-sized enterprises (SMEs), the findings of Hervás-Oliver et al. (2021a) suggest that innovation in lagging regions fundamentally relies on collaboration with external partners, either from within or outside the region.

Both these and other articles (e.g. Mitze et al., 2015; Grillitsch and Nilsson, 2015; Wassmann et al., 2016; Eder, 2019) imply that interactive learning is key to innovation activity in lagging regions (on the interactive model of innovation at the regional level, see e.g. Asheim and Parrilli, 2012). We therefore hypothesize that personality characteristics – and in particular such Big Five traits that relate to social interaction and collaborative behavior – are imperative for the innovativeness of lagging regions. To explore this hypothesis, our paper brings together two separate strands of literature by combining studies on the variability of regional innovation in terms of learning and modes of innovation (e.g. Isaksen and Trippl, 2017; Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021a; Parrilli et al., 2020) with the emerging literature on the relationship between aggregated Big Five traits and regional innovativeness (Lee, 2017; Mewes et al., 2022). In this way, our paper contributes to a better understanding of regional innovation capacity, especially regarding the case of lagging regions that are a main focus of regional policy.

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 and Costa Jr., 2008). There are five independent traits that have been shown to remain relatively stable over an individual's life span (Cobb-Clark and 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 and Collins, 1999; Lucas 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 towards being task-oriented, hardworking, and efficient. Emotional stability measures resilience in the face of setbacks, and openness indicates a willingness to experience novelty.

Aggregated personality data – usually generated by averaging the individual characteristics within a certain geographic area – have been widely used as an indicator of regional culture (Hofstede and 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 "culture" can be conceptualized and measured in terms of aggregated Big Five traits, it seems plausible that an increasing share of individuals with certain personality traits will affect the nature of interactions within a region. As Rentfrow et al. (2008) state, "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" (p. 341).

There are a variety of potential and complex causes for variation in personality patterns – both between and within regions over time – that are not yet fully understood by researchers. First, while the Big Five personality traits change little over individual lifespans (Cobb-Clark and Schurer, 2012; Rantanen et al., 2007; Wortman et al., 2012), some variability in individual traits over time exists. Rantanen et al. (2007) find that the mean level of extraversion, openness, agreeableness, and conscientiousness slightly increases between the age of 33 and 42, whereas mean neuroticism values decline. The correlations of the rank order of traits within a group of people for the same time period lies between 0.73 and 0.97. Specht et al. (2011) also find some age-related changes as well as changes in response to major life events. Individual personality changes can therefore be seen as a modest source of regional within-variation over time. Second, if an individual's age affects personality traits, the general aging of the German population – which is more pronounced in some areas than others (in particular in rural regions, see Studtrucker et al., 2022) – should also generate some within-region variation of aggregate personality traits over time. Third, due to urbanization, the influx of migrants and other reasons, the population composition within regions changes over time. For example, it has been shown that extraverted and open individuals are more likely to emigrate (Canache et al., 2013), and that immigrants in Germany tend to settle down in selective areas (Heider et al., 2020). In addition, Jokela (2009) shows that openness, agreeableness, and extraversion predict relocation decisions within the United States. Thus, we expect to observe changes in regional personality traits over time. Fourth, individuals' opinions and beliefs may be influenced by the attitudes and behaviors of those around them, suggesting that regional personality may change and develop through repeated social interactions with others (Rentfrow et al., 2008, 2013, 2015). For example, the social environment of a region (e.g. the degree and nature of cooperative activities) could influence average levels of extraversion because people may adopt behavioral and psychological tendencies in response (e.g. by becoming more interested in being part of a larger social network). Thus, existing regional personality patterns and features of the social environment might mutually reinforce each other, leading to regional variation in personality.

2.2. Interactive model of regional innovativeness

The emphasis of regional innovation policy on the promotion of R&D activities can be interpreted as a product of a linear model of innovation (Isaksen and Nilsson, 2013; Edler and Fagerberg, 2017; Hervás-Oliver et al., 2021a). However, it is now increasingly recognized that a broader perspective is needed to understand and explain the heterogeneity of regional innovation patterns (Isaksen and Trippl, 2017; Hervás-Oliver et al., 2021b).

One such an approach is offered by the interactive model of innovation, which – instead of a narrow focus on R&D and science-driven innovation – emphasizes the general stimulation of interaction and knowledge exchange between a variety of actors in regional innovation systems (Lundvall, 1992; Cooke, 2001; Asheim and Parrilli, 2012). Regions exhibit unique networks of innovation-related actors, such as firms with their respective knowledge bases and know-how, other organizations such as universities, research institutes and supporting infrastructures. Innovation is defined here as 'interactive learning' embedded in different modes of innovation: the STI mode (Science, Technology and Innovation) with its focus on R&D-based learning, the DUI mode (Doing, Using and Interacting) with an emphasis on non-R&D-innovation, and the various combinations of these two modes at the firm and regional levels (Jensen et al., 2007; Isaksen and Nilsson, 2013; Lundvall and Lorenz, 2012). Corresponding policy approaches focus on strengthening the intra- and interregional connectivity of regional innovation systems, e.g. by promoting joint innovation projects along the regional value chain (between producers, suppliers, users and customers) or intensifying interregional knowledge spillovers through building STI- and DUI-related absorptive capacities (Asheim and Parrilli, 2012).

A purely R&D and science-driven innovation policy promotes leading regions in particular, as these firms – unlike those in lagging regions – have the resources and STI-related absorptive capacities to carry out the intended processes of knowledge generation and exploitation (Asheim and Parrilli, 2012; Hervás-Oliver et al., 2021a; Hervás-Oliver et al., 2021b; Brenner and Niebuhr, 2021). Under these conditions, lagging regions run the risk of not receiving sufficient support, which is why an innovation policy based on the interactive model of innovation may be more suitable. Two specific features of lagging regions hold particular importance in this context: (1) a low share of business R&D, which is often associated with a weak regional knowledge infrastructure, and – related to this – (2) a dominance of SMEs and their often informal learning and innovation practices, which are strongly anchored in the DUI mode (Pelkonen and Nieminen, 2016; Isaksen and Trippl, 2017; Alecke et al., 2021; Barge-Gil et al., 2011; Santamaría et al., 2009; Hervás-Oliver et al., 2011; Hervás-Oliver et al., 2014; Hervás-Oliver et al., 2015). Learning in the DUI mode includes phenomena that take place within companies, i.e. internal DUI interactions such as exchanges between employees and departments, as well as external DUI interactions such as exchanges of application-oriented industry knowledge or cooperation with customers and suppliers (see Thomä and Zimmermann, 2020; Runst and Thomä, 2022; Bischoff et al., 2023; Alhusen et al., 2021). These internal and external interaction elements of DUI mode learning can be seen as a compensatory mechanism for the lack of STI-related absorptive capacity, and can thus be conceptualized as absorptive capacity in relation to non-R&D knowledge (Haus-Reve et al., 2022; Weidner et al., 2023; Bischoff et al., 2023b).

Several empirical studies have shown that interactive learning is a dominant driver of innovation in lagging regions, in terms of both STI interaction and DUI interaction (see Bischoff et al., 2023b). For example, Filippopoulos and Fotopoulos (2022) apply a fuzzy-set qualitative comparative analysis to Regional Innovation Scoreboard data. They suggest that lagging regions are relatively more dependent on public R&D, softer innovation aspects – such as tolerance and inclusion values – and networks of collaboration compared with leading regions. Hervás-Oliver et al. (2021a) focus on SMEs as they account for two-thirds of overall employment in the European Union and play a major role in regional innovation. They also use Innovation Scoreboard data to perform regression analysis, which enables them to explore 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. By contrast, SMEs in lagging regions fundamentally rely on collaboration with other firms and public research organizations.

Similarly, Wassmann et al. (2016) analyze firm-level data from low-tech micro firms in Germany. 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 strongly depends on innovation-relevant knowledge exchange with cooperation partners outside the region. Similarly, Grillitsch and Nilsson (2015) provide empirical evidence that firms in peripheral regions have reduced local access to innovation-relevant knowledge, and must therefore collaborate at other geographical scales to "compensate for the lack of access to local knowledge spillovers." Their Swedish sample based on the Community Innovation Survey contains 2261 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. According to their results, peripheral innovators are less likely to benefit from local knowledge spillovers and must therefore compensate for this deficiency by actively undertaking joint innovation projects.

Thus, there is ample evidence that firms in lagging regions can compensate for their lack of R&D – at least to some extent – by interactive learning, by either gaining new innovative impulses through collaboration with other (DUI or STI) actors within the region or tapping knowledge sources outside their region.

2.3. *The Big Five and their impact on interactive learning in regional innovation systems*

The firm-level literature provides evidence of a relationship between an individual's *openness* and *extraversion* score and their likelihood of becoming an entrepreneur (Zhao and Seibert, 2006; Nicolaou and Shane, 2010; Brandstätter, 2011; Caliendo et al., 2014; Runst and Thomä, 2023). At the regional level, the relevance of the two traits for entrepreneurship is confirmed by Tavassoli et al. (2021), who report that aggregate trait scores for openness and extraversion have a positive impact on the quality of entrepreneurship in US metropolitan areas. While not all entrepreneurs become innovators, and entrepreneurship quality might not be equivalent to innovation, these empirical findings point to the traits of openness and extraversion when it comes to venturing into unknown commercial territory, when breaking with old routines and creating new ones, which represents a prerequisite for innovation. There is also empirical evidence of a link between extraversion, openness, and innovation at the firm level (Runst and Thomä, 2022; Marcati et al., 2008) as well as the individual level (Stock et al., 2016; Zwick et al., 2017). Based on the interactive model of innovation described above, a similar relationship can be expected between these two traits and innovation at the regional level.

2.3.1. *Extraversion*

Fig. 1 depicts two different social networks (*A* and *B*) composed of various agents (indicated by the circles). An individual *I* with high levels of extraversion (orange circle) is more likely to develop a connection with other individuals within the intra- or interregional network, and may therefore be located closer to the network center. Certain parts (e.g. agent *III* within the rectangle) 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 *II* would critically benefit from access to agent *III*, who serves as a gateway to such an island with all its potential for interactive learning.

In Panel *B,* the extraverted version of agent *II* is represented as possessing a larger number of social ties than before, the previously unconnected island indicated by the rectangle is now accessible to agent *II*, and all information flows must pass through this node to reach all other agents. Within the context of regional innovation, agent *II* (as well as agent *III*) is therefore uniquely situated and should exhibit a higher likelihood of innovation, the benefits of which should in turn 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, both within one's own region and in exchanges with other regions. By 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 of accessing 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

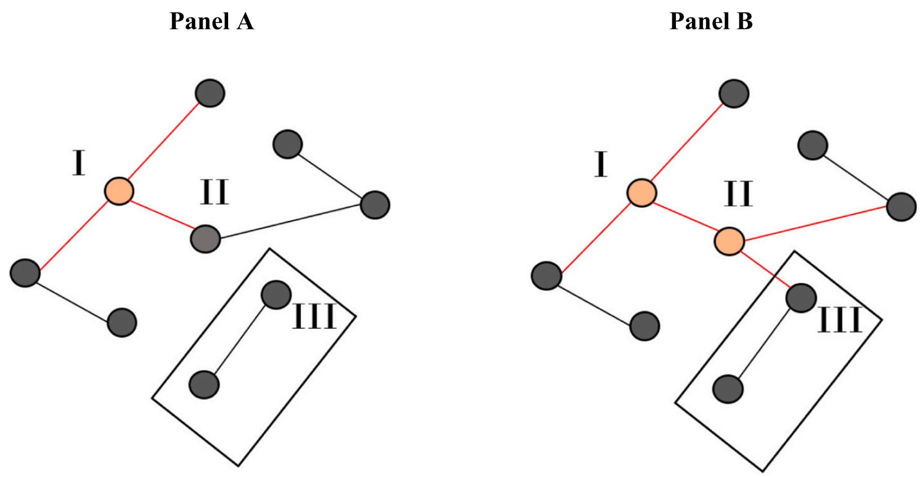

Fig. 1. Information flows and exchange in two distinct networks
Notes: Gray nodes represent non-extraverted individuals, who may – for example – work within firms, represent customers, or work as researchers in universities. Orange nodes represent extraverted actors, who possess a larger number of social ties (i.e. connections to other actors). Information can only flow along social ties. Islands (e.g. the rectangle) comprise actors or sub-networks that remain unconnected to other parts of the network and the knowledge within can only be accessed by actors who successfully bridge the gaps between them.

should also indirectly support innovation by stimulating higher levels of cooperation.

Thus, regions with a higher share of extraverted individuals – a trait that is primarily linked to sociability and social interaction – are likely to be associated with higher levels of communication, collaboration[1] and knowledge exchange because they possess an increased number of social connections (or ties) between individuals, firms or other agents.

Importantly, as noted above, the positive effects of a higher network density (as in Panel *B*) should accrue both within and across regions, reflecting the overall connectivity in regional innovation systems (Asheim and Parrilli, 2012). An improved network connectivity of relevant actors – such as competing firms, universities, suppliers, and customers – can spur innovation if all of them are located within the same region. However, regarding lagging regions in particular, it can be argued that connectivity increases the potential for innovation, even more so when external sources of knowledge in other regions can be accessed, especially in cases where local innovation capacities are less developed (Grillitsch and Nilsson, 2015; Wassmann et al., 2016).

2.3.2. 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 and thus the degree of interactive learning in a region. Regions with higher aggregate levels of openness should therefore contain more entrepreneurs who monitor their external environment for new ideas and promising technologies (Sung and Choi, 2009; Zhao and Seibert, 2006). If agent *II* in Fig. 1 receives knowledge from agent *III* that was hitherto unavailable to any other agent in his network, 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 of Mewes et al. (2022).

[1] At this point, it is important to note that collaboration can mean both intraregional and interregional exchange relationships, and can be related to both STI (e.g. R&D cooperation with universities or other external scientific institutes) and DUI (e.g. collaboration with customers, suppliers and competitors) types of interaction.

2.3.3. Conscientiousness

The regionally aggregated trait of conscientiousness can theoretically affect innovation via its association with a commitment to a productivity enhancing work ethic (Lee, 2017). 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 and Moreno, 2015). Indeed, Lee (2017) finds evidence of a positive relationship between levels of conscientiousness and patenting activity in English and Welsh travel-to-work areas. This is noteworthy 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 adherence to established business models, 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, these theoretical and empirical considerations are ambivalent and we therefore do not formulate a hypothesis with respect to the conscientiousness trait.

2.3.4. Agreeableness and neuroticism

Similarly, the two traits of agreeableness and neuroticism do not lend themselves to a clear theoretical prediction. 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. Finally, *neuroticism (antonym: emotional stability)* measures an individual's susceptibility to stress and tension. Given a marked lack of empirical evidence when it comes to the relationship between this trait and entrepreneurship or innovation, we do not formulate any hypothesis in this regard.

2.4. 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 greater in lagging regions than in leading regions, as the low levels of R&D and a dominance of SME innovation mean that interactive learning with DUI partners such as other companies and customers and STI partners such as universities or other public research institutes plays a key role in generating innovation there (see Section 2.2). As outlined above, there is evidence that innovative firms in lagging regions are more dependent on collaboration with external partners to overcome their internal lack of capabilities (Bischoff et al., 2023; Bischoff et al., 2023b; Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021a; Mitze et al., 2015; Grillitsch and Nilsson, 2015; Wassmann et al., 2016; Eder, 2019).

We therefore hypothesize that personality traits that support interactive learning are especially important for innovation in lagging regions. By increasing the connectivity of relevant actors, they create the preconditions for successful collaboration, and thereby serve as a compensatory mechanism for the lack of R&D-related resources and capacities. Extraversion in particular should increase the number of connections between agents in the innovation system of lagging regions and enable or improve corresponding knowledge flows along networks of collaboration (see Section 2.3). While openness has also been argued to increase knowledge flows along existing network connections – a property that may well facilitate interactive learning – 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, these firms are often engaged in application-oriented cooperation driven by 'development' rather than 'research' (Wassmann et al., 2016). Since the degree of novelty is likely to be relatively low, the degree of openness may be less important. After all, the degree of openness required to implement external ideas that have proved successful elsewhere need not be quite so high.

3. Data and methods

3.1. Data

We use data on the Big Five Project by Peters and Matz (2022)[2] and the German Socio-Economic Panel (GSOEP) for information on Big Five (BF) personality traits. As a well-established indicator for innovation, our dependent variable, we use patent application data that is available via the German Patent and Trade Mark Office (DPMA) and the European Patent Office (EPO).[3] 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).

The data collected in the Big Five project provides detailed information on BF traits, measured on a 44-item scale (the BF-44[4]), at the regional level. It has been used by a number of papers in psychology and economics (e.g. Obschonka et al., 2013, 2018) and was collected between 2002 and 2015 via a website (see Gosling et al., 2004). It has also been used to describe regional personality patterns in Germany (see Obschonka et al., 2019a).

As a long-running international online survey, the BF project's survey data contains a very large number of observations, but unfortunately individual answers are not time-coded. We therefore also use a second source of regional BF scores based on individual-level BF survey items available in the GSOEP for 2005, 2009, 2012, 2013, and 2017. In each year, fifteen items (the BF-15) were surveyed in the GSOEP, three of which are associated with a specific Big Five trait. Small item scales such as the BF-15 retain significant levels of reliability and validity compared with longer versions such as the BF-44 (Rammstedt and John, 2007). There are about 11,500 individuals with complete BF traits in 2005, which increases to about 14,000 in 2017. Following Runst and Thomä (2022), 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. The choice of RORs as our primary regional level of analysis is driven by the available number of panel survey answers from the GSOEP, which would have been insufficient for a regional analysis at a lower spatial level. For years without GSOEP-based BF trait information, we linearly interpolate traits values (and extrapolate for 2018). Therefore, while the GSOEP personality data allows us to create a panel data set, one could argue that the number of trait observations in certain regions is somewhat small. By using this dataset, we therefore obtain a panel structure compared to the BF project data of Peters and Matz (2022), but lose measurement precision.

The mean number of individuals with BF trait information per region is 142, although 84 region-year observations do not fulfill an $n \geq 40$ criterion, which we therefore exclude from the analysis. Moreover, for two planning regions, data is only available from 2011 onwards, reducing the sample by another twelve observations. Fig. A.1 in the Appendix displays all 96 German planning regions and their corresponding number of annual observations with a minimum of 40 responses. There is no single region that is always missing in all years, and sixteen regions are only included only in three to eleven years, but 80 regions are included in all fourteen years of observation. Missing region-year observations are relatively evenly distributed across geographic space, although it is somewhat noticeable that – for obvious reasons – observations from less densely populated rural regions tend to be missing more often. Against this background, we conclude that the omission of the 84 region-year observations does not systematically bias our results. The final dataset is a panel with 1332 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.

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. Figure shows how the DPMA patent applications are distributed across German planning regions. As expected, many patents are filed in the South, while the East and the coasts record the fewest applications. 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 (Fig. 2).

Gross expenditure on R&D (GERD) by companies, governments and universities is provided by Eurostat and only available at the NUTS2 level. 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

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

[3] 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).

[4] There are different Big Five inventories such as the BF-44 or the BF-15, which differ in the number of items used to measure the Big Five.

[5] https://register.dpma.de/

[6] https://www.epo.org/

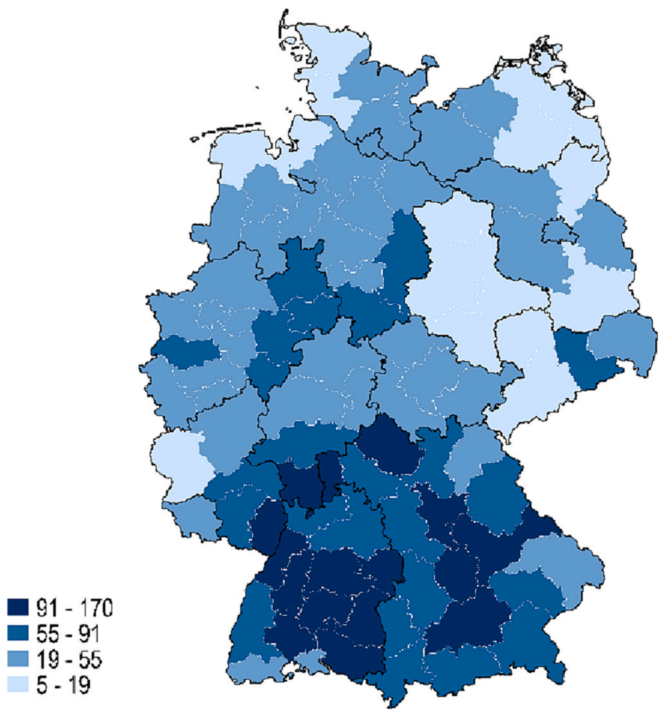

Fig. 2. DPMA patent applications per 100,000 inhabitants (by planning region, 2005–2018 average)
Source: DPMA.

taken from the Federal Statistical Office. The employment share in manufacturing as well as the number of students are provided by the INKAR regional database.[7] Data on non-R&D expenditures has been obtained from the Regional Innovation Scoreboard (RIS) of the European Commission.

Descriptive statistics of all variables are summarized in Table 1. A variance decomposition shows that between-region variation accounts for >90 % of the total variability in the dependent variable as well as all explanatory variables except the regional BF (see Table A.2). Regionally aggregated BF traits exhibit about 50 % between- and 40 % within-variation (see also Section 2.1 for a discussion of the variability of regional Big Five data).

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

Variable	Source	Mean	Std. Dev.
Patents per 100,000 inhabitants (log)	DPMA	3.767	0.750
Patents per 100,000 inhabitants (log)	EPO	2.544	0.836
Big Five (Factor scores)			
Extraversion	GSOEP	0.000	0.093
Conscientiousness	GSOEP	0.019	0.110
Neuroticism	GSOEP	0.003	0.089
Openness	GSOEP	−0.001	0.098
Agreeableness	GSOEP	0.005	0.102
Big Five (item averages)			
Extraversion	Peters and Matz (2022)	3.384	0.066
Conscientiousness	Peters and Matz (2022)	3.462	0.053
Neuroticism	Peters and Matz (2022)	3.040	0.058
Openness	Peters and Matz (2022)	3.710	0.051
Agreeableness	Peters and Matz (2022)	3.429	0.039
Population density (log)	Federal Statistical office	5.39	0.853
Share of manufacturing employment	INKAR	0.235	0.082
Number of Students per 1000 inhabitants	INKAR	25.933	17.199
Gross expenditure R&D business per 100,000 inhabitants (log)	Eurostat	56.191	59.915
Gross expenditure R&D government per 100,000 inhabitants (log)	Eurostat	3.603	0.912
Gross expenditure R&D tertiary per 100,000 inhabitants (log)	Eurostat	2.023	1.134
Non-R&D innovation expenditure (percentage of turnover) (log)	RIS	2.575	0.671

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 linearly. 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

For the cross-sectional data of the BF project (Peters and Matz, 2022), we run ordinary least squares regression. In case of the GSOEP panel data, we use fixed effects regression, where the dependent variable is the logarithm of the number of patents per 100,000 inhabitants. There are 94 planning regions for 2005–2018. Due to missing variables, there are 1208 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. 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 the logarithm of population density, the logarithm of gross expenditure on R&D (GERD) per 100,000 inhabitants, 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]

Fixed effects regression accounts for unobserved regional-level heterogeneity over time, i.e. region fixed effects. Such a design relies on within-subject variation of the data. Some argue that by removing the between-subject variation one may ignore relevant variation contained in the dataset (see Bell and Jones, 2014). In response to a referee request, and as a robustness test of our fixed effects results, we additionally estimate a within-between random effects (REWB) model, originating from Bell and Jones (2014) and Mundlak (1978), which captures both within- and between-subject effects between personality and regional innovativeness (for a recent application of this model, see e.g. Fotopoulos, 2022)[9]:

$$y_{rt} = \beta_0 + \beta_1(x_{rt} - \overline{x}_r) + \beta_2\overline{x}_r + (u_r + \varepsilon_{rt})$$

This model specification permits us to explicitly model the between-subject effect (β_2) by generating the region-specific mean of covariates over time, and the within-subject effect (β_1) by de-meaning covariates. However, there is an ongoing debate about the proper use of REWB models. It has been argued that the between-effects in particular contain no informational content in panel data analysis, as opposed to multi-

[7] https://www.inkar.de/

[8] A correlation matrix can be found in the Appendix (Table A.3).

[9] A variance decomposition of the regression variables can be found in Table A.2 in the Appendix. See section 3.1 for a discussion of this.

Table 2
Cluster analysis results.

	Cluster		
	I	II	III
Gross expenditure R&D business per 100,000 inhabitants (log)	3.921	3.102	4.600
Gross expenditure R&D tertiary per 100,000 inhabitants (log)	1.699	2.340	3.147
Gross expenditure R&D government per 100,000 inhabitants (log)	2.639	2.610	3.238
Patents normalized by population (log)	4.069	3.197	4.278
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
Intensity of non-R&D innovation expenditure (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.

level research where they may be more applicable,[10] which is why some researchers argue in favor of not interpreting between-effects or not reporting them at all (Krause and Urban, 2013; Allison, 2017; Schunck and Perales, 2017; Auspurg et al., 2019; Brüderl and Ludwig, 2019). Moreover, the omitted variable bias is potentially larger in the case of time invariant variables as in a REWB model setting "unmeasured level 2 characteristics [time invariant characteristics] can cause bias in the estimates of between effects" (Bell et al., 2019, p. 1059). We therefore refrain from interpreting between-effects in our REWB models and focus on the within-effects of regional personality.

3.3. Regional innovation typology

Finally, according to the discussion above, we expect the effect of extraversion on innovation to be particularly strong in lagging regions. We therefore use a cluster analysis to divide the regions in our sample according to different region types that consider a region's level of economic development and its innovation mode (for similar classifications of regions, see e.g. Hertrich and Brenner, 2023; Koschatzky and Kroll, 2019). This clustering procedure is based on the following innovation-related variables: 1) population-normalized R&D expenditure by private actors, alongside that of the state and universities; 2) the intensity of non-R&D-related innovation expenditures (share of turnover); 3) the log of patents normalized by population; 4) gross domestic product (GDP) as a general indicator of 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 2012 to 2018, as no values are available for earlier years. We seek to capture innovation that is not only related to R&D (i.e. STI mode). To capture the relative prevalence of the DUI mode, we use variables on non-R&D innovation expenditure and vocational training, as previous research has shown corresponding relationships (e.g. Thomä, 2017; Thomä and Zimmermann, 2020; Matthies et al., 2023). This allows us to include not only R&D-oriented (STI) types of interaction but also DUI-based types of interactive learning in the context of regional innovation activity (Hervás-Oliver et al., 2021a).

The complete use of our panel data set in a clustering procedure

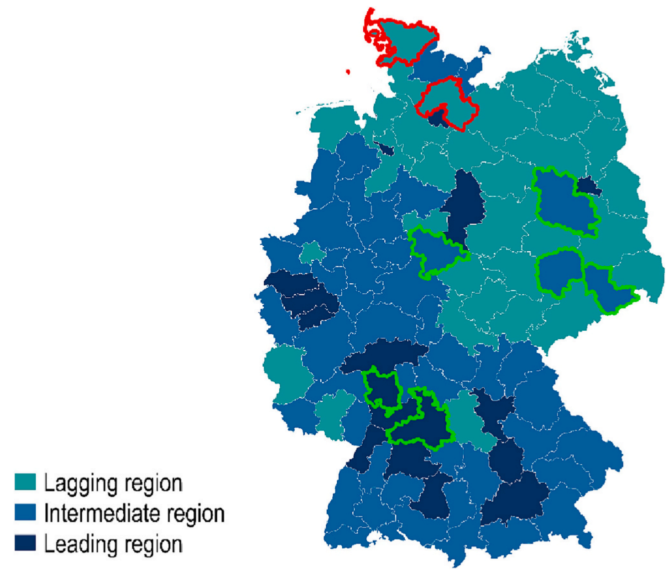

Fig. 3. Region types from cluster analysis in 2018
Notes: Colorful borders signify a change in the type of innovation in the period (2012 to 2018). Light green represents an improvement, whereas red represents a decline. The filling color of regions with changing innovation status signifies the innovation type at the end of the time period (2018).

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 whether regions move between innovation modes over time, which is quite probable in the course of regional development processes.

We therefore dismiss both approaches and perform separate cluster analyses for 2012, 2015, and 2018, filling in missing years with the last available information on the regional innovation mode. 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 Jr. 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 as 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 made up of urban regions, as population density is highest in this group. The opposite is true for the second cluster, as it has the lowest values for all cluster variables except vocational training, while public R&D and non-R&D innovation are still relatively high. It is therefore referred to as the "lagging cluster" and it tends to comprise rural or peripheral regions. In line with the above discussion, we therefore assume that innovativeness of lagging regions – at least in relative terms – is strongly influenced by the DUI mode of innovation.

[10] It should be noted that the data in our main specification does not have a multi-level structure, as we are not operating with individual data nor on multiple regional levels within a single model (see Section 3.1).

Table 3
Regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Years	2018	2018	2005–2018	2005–2018	2005–2018	2005–2018	05, 09, 12, 13, 17	2005–2018	2005–2018
Extraversion	5.267***	2.077**	6.427***	0.325***	0.281***	0.263**	0.211	0.228***	0.228***
Conscientiousness	−2.753*	1.000	−3.783**	−0.104	0.060	0.084	0.019	0.097	0.097
Neuroticism	−1.465	0.354	−0.365	0.005	0.087	0.023	−0.094	0.082	0.082
Openness	0.640	1.064	−2.174	−0.270**	−0.235**	−0.191*	−0.104	−0.204**	−0.204**
Agreeableness	1.014	−0.745	−3.060	0.244	−0.010	−0.090	−0.117	−0.081	−0.081
Population density		0.068	−0.299**		−1.010***	−1.089***	−1.047***	−0.694***	−0.694***
Manufacturing		3.552***	2.060***		0.842	1.608	2.102	−0.005	−0.005
Students		0.002	−0.000		−0.001	0.001	−0.000	0.001	0.001
R&D business (log)		0.466***	0.182***		−0.046	−0.038	−0.068	0.113***	0.113***
R&D government (log)		−0.025	0.061***		0.022	0.014	0.031	0.014	0.014
R&D tertiary (log)		−0.091	0.036		−0.008	−0.056	−0.052	0.072***	0.072***
Constant	−5.720	−11.710	15.055	3.745***	9.131***	9.605***	9.329***	3.758***	6.856***
N	96	96	1288	1248	1211	983	356	1211	1211
R^2	0.312	0.748	0.387	0.382	0.636	0.703	0.693		0.290

Notes: Patent data was obtained from the German patent office (DPMA). Specifications (1) to (3) use survey data of the Big Five project provided by Peters and Matz (2022), whereas columns (4) to (9) use GSOEP BF variables. 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. Columns (4) to (7) include year and planning region fixed effects. In columns (1) to (7), standard errors are clustered by planning region. Columns (6) and (7) restrict the sample to a minimum of 70 survey respondents in the GSOEP per year and planning region to exclude regions with a small number of observations. Column (7) further restricts the sample to including only the years for which the GSOEP data on the Big Five is available (2005, 2009, 2012, 2013 and 2017). Column (8) applies uses a REWB model and reports within-effects, column (9) is a fixed effects regression specification without year fixed effects. Significance levels: *, **, *** indicate significance at levels of 0.10, 0.05 and 0.01.

The "intermediate cluster" (cluster *II*) 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 or peripheral and may be characterized by a combinatorial mode of innovation.

Fig. 3 shows the change in regional cluster affiliation between 2012 and 2018. Most strikingly, almost the entire East of Germany comprises lagging regions, whereas leading regions are concentrated in the South. The six regions outlined in green – predominantly located in the East and South-West – 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.

4. Results

4.1. Baseline regression

As described above, in a first step we use regional traits values based on the BF project (specifications (1) to (3) in Table 3). According to the corresponding results, the extraversion coefficient is the only one that is consistently and significantly different from zero. In specification (2), a one-unit increase in extraversion leads to an increase in the log of patents by about 2.1. In other words, an increase in extraversion by one standard deviation (0.066) increases the number of patents by around 15 %. The conscientiousness coefficient is negative and significant in columns (1) and (3), and insignificant in column (2), thereby not displaying a consistent effect across all specifications. Similarly, the three remaining personality traits of neuroticism, openness, and agreeableness do not display coefficients that are different from zero.

The results of the fixed effects regressions – using GSOEP data as a source of BF traits – are shown in specifications (4) to (7) in Table 3, including both planning region and year fixed effects. For the purpose of robustness testing, columns (6) and (7) restrict the sample to a minimum of 70 BF survey responses per region and year. Specification (7) further reduces the panel data to the five years in which BF survey responses are available. Column (8) shows the within-effects from a REWB model (for more details, see Table A.7 in the Appendix), which correspond to those in column (9), where the fixed effects specification from column (5) is concerned and the year fixed effects are now excluded from the regression. Across these different specifications, extraversion is the only personality trait that is consistently significant, except in column (7) for the reduced sample on the actual years, where we see a positive coefficient on extraversion that is close to the 10 % level. Extraversion effect sizes are moderate to large: when extraversion increases by one unit in the specification of column (5), patent applications approximately increase on average by around 28 %.

Besides extraversion, none of the other BF traits exerts a significant and consistent effect across the different specifications shown in Table 3. The negative and significant effect of openness on patent applications in specifications (4) to (6), (8) and (9) is surprising, as upon first glance it seems to show the opposite of what Mewes et al. (2022) found in the case of breakthrough innovations. However, as it is not consistent across all specifications, it must be interpreted with caution.

The coefficients of the control variables in our main specification (5) are mainly insignificant, except for population density, which negatively influences regional innovativeness in terms of patenting, except for specification (2). The coefficient on the population-normalized private R&D expenditure is positive and significant, but only in columns (2) and (3), which rely on cross-sectional or random effects regression, as well as in columns (8) and (9), where we run REWB regression or FE regression without year fixed effects and – in both specifications – without robust standard errors.[11]

4.2. Heterogeneous effects of the regional innovation type

To examine whether personality is more important for the innovativeness of lagging regions (see Section 2), we run our main fixed effects regression specification (column (5) in Table 3 based on GSOEP BF characteristics) separately for the three identified region types (see Table 4). Specification (1) to (3) uses all years, whereas (4) to (6) restrict the sample to the years in which BF survey data exists. The cluster of lagging regions yields a positive and significant coefficient for extraversion (columns (2) and (5)), which – as expected – indicates that

[11] We exclude robust standard errors to show the equivalence of REWB and FE estimates.

Table 4
Results of the fixed effects regression performed separately for the three clusters.

	(1)	(2)	(3)	(4)	(5)	(6)
	2012–2018	*2012–2018*	*2012–2018*	*2012, 13, 17*	*2012, 13, 17*	*2012, 13, 17*
	Intermediate region	Lagging region	Leading region	Intermediate region	Lagging region	Leading region
Extraversion	0.175	0.595***	0.024	0.057	0.545***	0.630*
Conscientousness	−0.041	0.336	0.322	−0.007	0.248	0.159
Neuroticism	0.110	0.119	0.406	−0.077	0.271	0.497*
Openness	−0.086	−0.482**	0.707	0.061	−0.192	0.322
Agreeableness	0.119	0.097	−0.201	0.163	−0.164	−0.174
Population density	0.236	−0.557	3.536	0.526	−0.268	1.603
Manufacturing	−0.419	−0.809	−5.721	−0.921	3.072	−0.165
Students	0.001	−0.001	−0.007	0.007	−0.001	−0.004
R&D business (log)	−0.156**	0.072	0.072	−0.167	0.024	0.124
R&D government (log)	0.041*	−0.195*	0.155	0.135**	−0.147	0.574
R&D tertiary (log)	−0.045**	−0.048	0.324	−0.018	0.024	0.662*
Constant	3.410	6.283	−18.951	1.641	3.998	−10.448
N	330	220	107	140	96	45
R^2	0.600	0.501	0.797	0.541	0.584	0.825

Notes: Patent data was obtained from the German patent office (DPMA). Based on specification (5) in Table 3, the fixed effects regression has been run separately for the three clusters 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 level ofs 0.10, 0.05 and 0.01. Cluster regressions in columns (1) to (3) contain the years 2012 to 2018; columns (4) to (6) only contain the years 2012, 2013 and 2017 in this time frame for which GSOEP data on the Big Five is available.

Table A.2
Variance decomposition of variables.

Variable	Between	Within	Residual	Model
Patents (log)	93.75 %	4.52 %	1.73 %	98.27 %
Extraversion	50.42 %	41.83 %	7.74 %	92.26 %
Conscientiousness	52.12 %	40.29 %	7.59 %	92.41 %
Neuroticism	51.26 %	41.08 %	7.66 %	92.34 %
Openness	48.86 %	43.20 %	7.94 %	92.06 %
Agreeableness	51.13 %	41.20 %	7.67 %	92.33 %
Population density	98.56 %	0.87 %	0.56 %	99.44 %
Manufacturing	98.13 %	1.18 %	0.69 %	99.31 %
Students	91.82 %	6.06 %	2.12 %	97.88 %
R&D business (log)	91.80 %	6.06 %	2.14 %	97.86 %
R&D government (log)	92.90 %	5.19 %	1.91 %	98.09 %
R&D tertiary (log)	79.84 %	16.08 %	4.07 %	95.93 %

Notes: Based on specification (5) in Table 3.

extraversion plays an important role for innovation in lagging regions, albeit not consistently so in the intermediate or leading regions.[12] The openness coefficient is negative and statistically significant in column (2) only. As expected, the effect of openness is positive in the case of leading regions, but is not statistically significant.

When using the BF data from Peters and Matz (2022), the sample size in the cross-sectional data becomes quite small after splitting into three region types. Therefore, in this case we use interactions between region type and BF traits instead of split-sample regressions (see Table A.8). We still see a positive effect for extraversion only in the lagging regions. Overall, the coefficient for extraversion is larger in the sample of lagging regions than in our baseline regression, confirming our hypothesis that the relationship between personality and regional innovativeness is particularly strong in the less R&D-intensive environments of lagging regions. None of the other BF variables display any statistically significant coefficients in Table A.8, except for a positive and weakly significant interaction between leading regions and conscientiousness, in a finding that seems to be consistent with Lee (2017).

As a robustness check, Table A.9 in the Appendix also uses a split-sample REWB design in which the BF traits are allowed to exert different effects across region types. Again, only lagging regions display a positive extraversion within-effect, both when using all panel years (specification 2) and when using only the years for which GSOEP BF trait information is available (specification 5).

4.3. Further robustness tests

We use data on European patent applications (EPO data) as an alternative dependent variable. Our baseline fixed effects regression results remain robust and yield a significant extraversion coefficient (Table A.10 in the Appendix), albeit only at the 10 % level. Moreover, 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.11). We also address the modifiable areal unit problem (MAUP) by running the baseline specification based on Peters and Matz (2022) BF data at the county level (Table A.12). All of these results are in line with the above findings on the extraversion effect.

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.13 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 and 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 weight 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 weight 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.13). The results prove to be robust to spatial autocorrelation across all four specifications. In addition, we find a positive and significant impact of the spatial lag of extraversion on patenting, suggesting that neighboring region's j extraversion positively affects innovation in one's own region i. This constitutes some evidence in favor of border-crossing social networks.

The next robustness check relates to the three distinct types of regions. First, we exploit the fact that innovation activity and structural weakness of a region are related (Koschatzky and Kroll, 2019). The regression results on the extraversion-innovation effect prove to be robust when regions are divided based on their population density, GDP, and the region-type classification according to the Federal Office for Building and Regional Planning (BBSR), all of which yield robust results with respect to the role of extraversion for innovation in lagging regions

[12] Extraversion is weakly statistically significant for leading regions in column (6), although this specification suffers from a very small number of observations and the effect is not robust to alternative region classifications (see Table A.14).

(Table A.14).

We also split the sample of lagging regions into those in former East and West Germany.[13] We find positive and significant effects of extraversion on patenting in both cases (Table A.15), supporting the argument that we are indeed analyzing a phenomenon that applies to lagging regions in general and is not specific to eastern German regions in terms of their socialist legacy.

Finally, we explore spatial heterogeneity by applying a geographically weighted panel regression (GWPR) in which multiple regional samples are drawn to estimate regionally specific coefficients.[14] The algorithm iterates through all regions *i*, generating a sample by including other regions *j* within a certain distance from *i*. Regional observations *j* are weighted more strongly if they are closer to *i* and are weighted less strongly if they are further away. Fig. A.2 in the Appendix shows the results of the GWPR with an adaptive bandwidth of 62 regions, although the results are similar when we use an optimal fixed bandwidth of 352 km. Extraversion has a positive and significant effect on patent applications in central and eastern Germany, and its effect size becomes larger towards the East (see Fig. A.2, 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 further support the robustness of our hypothesis on role of extraversion for innovation lagging regions 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 South, whereas it has a negative impact in some Western regions. The effect of neuroticism diagonally splits Germany into two parts, whereby the coefficients are positive and significant in the North-West, and negative in the South-East. Openness divides Germany horizontally and exhibits significant negative effects in the Northern half (see Fig. A.2, Panel D). Agreeableness only has a significant (positive) effect in few regions in the North-East and 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.

5. Conclusion

This paper has examined the relationship between personality and regional innovativeness in a two-stage procedure by first looking at the general effect of aggregate BF scores on regional patenting levels and then addressing the variability in this effect with respect to the 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 using the BF for cross-cultural or cross-national comparisons (e.g. McCrae, 2001; Hofstede and McCrae, 2004; Rentfrow et al., 2015; Obschonka et al., 2019b).

Furthermore, based on the interactive model of innovation, we argue that extraversion in particular increases the connectivity of innovation systems in lagging regions by enhancing communication, knowledge sharing and collaboration both within and across regions. Our empirical results on this question confirm that the relationship between personality and regional innovativeness depends on the type of 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 in the case of extraversion supports recent studies showing that interactive learning is an important driver of development and innovation in lagging regions (e.g. Bischoff et al., 2023; Filippopoulos and Fotopoulos, 2022; Hervás-Oliver et al., 2021a; Hervás-Oliver et al., 2011; Hervás-Oliver et al., 2014; Hervás-Oliver et al., 2015). We conclude from this that the aggregate regional level of extraversion spurs interactive learning, which in turn serves as a compensatory mechanism for a lack of R&D in less developed areas. This evidence of a regional extraversion-innovation link fits well with Runst and Thomä's (2022) findings that SME innovation in less R&D-oriented, DUI-based knowledge environments is strongly related to the personality of SME owners.

This implies that an innovation policy approach for lagging regions should extend beyond a narrow R&D focus and consider the strong interactive component of innovation activities in this specific type of region. A starting point for this is the fact that innovation in lagging regions is driven by less R&D-intensive SMEs, whose innovation activities are embedded in the so-called DUI mode of learning and innovation (Thomä and Zimmermann, 2020). Accordingly, innovation policies for lagging regions may promote organizational and inter-organizational learning and cooperation between producers and users (Isaksen and Nilsson, 2013). At the same time, it is important to support DUI-oriented SMEs in lagging regions through measures targeting both DUI (customers, suppliers, competitors) and STI (universities or other external research institutes) types of interaction to unlock the corresponding innovation potential. Thus, only by taking on a broader perspective that considers interactive learning across different modes of innovation will it be possible to provide useful inter- and intraregional policy impulses for lagging region innovation.

Corresponding policy approaches need to be place-sensitive, as interactive knowledge flows – especially in the context of the DUI mode – tend to be highly localized (Jensen et al., 2007). For this reason, it is precisely a bottom-up policy approach that could strengthen the innovation capacity of lagging regions by promoting more effective collaborations. For example, funding local alliances could bring together a wide range of actors from all parts of a lagging region's innovation system, who – unlike higher-level policy-makers – have time- and context-specific knowledge of their own region. The result could be regionally adapted measures and projects that consider region-specific structures and actor constellations (i.e. a "place-based policy"). If necessary, this promotion of collaborative innovation activities can also involve partners from outside the region to ensure external innovation impulses. As a result, regionally adapted development strategies can be created for lagging regions that are characterized by a high innovation potential.

The implications for managers are directly related to this. As mentioned above, our results complement the study by Runst and Thomä (2022) by showing how personality affects interactive learning, which can be used as a compensation mechanism for a lack of internal R&D resources not only at the firm but also the regional level. Business owners from lagging regions in particular should therefore take our findings as encouragement not to persist in a deficit perspective or try to follow innovation paths that are inconsistent with the regional status quo, but rather to focus on interactive learning within and across regions. The active participation and shaping of exchange formats and broader regional networking structures can potentially unlock the existing interactive learning potential of a lagging region, and thus be the key to innovation success for the companies located there.

One possible limitation of our study is that we examine the relationship between personality and regional innovativeness by using

[13] Due to the region fixed effects, we cannot simply include a control for a region being formerly under socialist regime.

[14] We used the 'GWPR.light' algorithm in the statistical software package R. As the package is currently non-functional (November 2023), we have no choice but to present an older version of the GWPR results from an earlier stage of the review process, in which we had not linearly interpolated the data (and R&D expenditure was not population normalized), but used the last available lagged value.

patenting as a measure of innovation (on the possible disadvantages of patents as an indicator of innovation, see e.g. Griliches, 1990). For lagging regions in particular, we suspect that much of the innovation activity occurs without patents and thus beyond the STI mode (Jensen et al., 2007; Hervás-Oliver et al., 2021b). Future research should examine this relationship by measuring regional innovativeness more comprehensively by constructing dependent variables that cover both DUI and STI types of learning and corresponding innovation outcomes. Finally, the search for a suitable instrumental variable for extraversion would be a promising starting point for future research to avoid potential endogeneity problems in the causal interpretation of our results.

CRediT authorship contribution statement

Leonie Reher: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Petrik Runst:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Jörg Thomä:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Appendix

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

		Extraversion	Conscientuousness	Openness	Agreeableness	Neuroticism
	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).

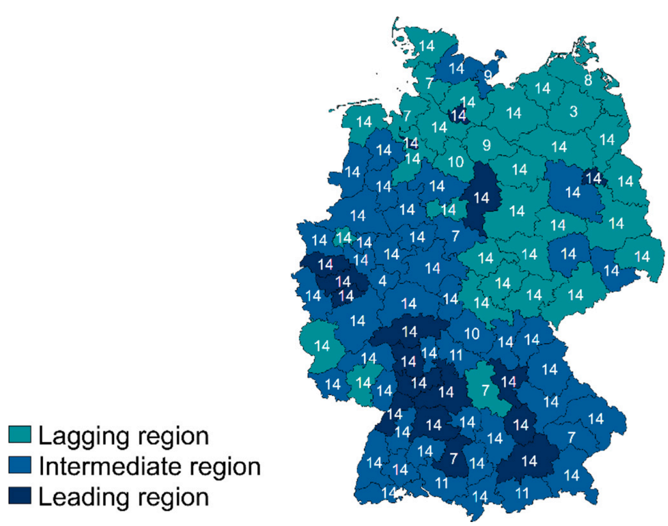

Fig. A.1. Years of observation per planning region.
Notes: Numbers in each planning region represent the number of years in which the region has at least 40 respondents to the survey. The maximum number of years is 14, or – in two cases (because data is only available from 2011) – 8 years. For the categorization into lagging, intermediate and leading regions, see Section 3.3.

Table A.3
Covariance matrix of regression variables (Pearson correlation).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Patents (log)	1.000											
(2) Extraversion	−0.137	1.000										
(3) Conscientiousness	−0.216	0.366	1.000									
(4) Neuroticism	−0.233	−0.259	−0.139	1.000								
(5) Openness	−0.083	0.429	0.082	−0.044	1.000							
(6) Agreeableness	−0.031	0.197	0.464	−0.190	0.171	1.000						
(7) Population density	0.162	0.054	−0.241	−0.020	0.194	−0.068	1.000					
(8) Manufacturing	0.593	−0.104	−0.012	−0.145	−0.145	0.005	−0.188	1.000				
(9) Students	0.087	−0.003	−0.190	−0.110	0.109	−0.053	0.448	−0.238	1.000			
(10) R&D business (log)	0.724	−0.153	−0.312	−0.155	0.055	−0.104	0.267	0.372	0.150	1.000		
(11) R&D government (log)	−0.050	−0.092	−0.021	0.138	0.033	0.061	0.112	−0.347	0.178	0.274	1.000	
(12) R&D tertiary (log)	0.118	−0.005	−0.058	0.049	0.178	0.085	0.217	−0.106	0.365	0.397	0.634	1.000

Notes: Covariance matrix of variables used in specification (7) of Table 3.

Table A.4
Covariance matrix of split regression variables – intermediate regions (Pearson correlation).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Patents (log)	1.000											
(2) Extraversion	−0.293	1.000										
(3) Conscientiousness	−0.061	0.386	1.000									
(4) Neuroticism	−0.062	−0.205	−0.122	1.000								
(5) Openness	−0.109	0.311	0.105	0.039	1.000							
(6) Agreeableness	0.043	0.010	0.323	−0.131	0.120	1.000						
(7) Population density	−0.022	0.010	−0.145	0.180	−0.029	0.024	1.000					
(8) Manufacturing	0.712	−0.196	0.063	−0.040	−0.053	0.097	−0.300	1.000				
(9) Students	−0.050	0.003	−0.184	−0.036	0.068	−0.108	0.441	−0.282	1.000			
(10) R&D business (log)	0.648	−0.214	−0.121	−0.130	0.006	−0.119	−0.080	0.432	−0.074	1.000		
(11) R&D government (log)	0.092	−0.086	−0.073	−0.037	0.128	0.034	0.277	−0.143	0.078	0.381	1.000	
(12) R&D tertiary (log)	0.209	−0.091	−0.105	0.021	0.153	−0.006	0.177	0.012	0.256	0.395	0.691	1.000

Notes: Covariance matrix of variables used in the split regression using regions from the intermediate cluster (Table 4 column (4)). Spearman correlation coefficient results are available from the authors upon request.

Table A.5
Covariance matrix of split regression variables – lagging regions (Pearson correlation).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Patents (log)	1.000											
(2) Extraversion	0.258	1.000										
(3) Conscientiousness	−0.092	0.244	1.000									
(4) Neuroticism	−0.299	−0.265	0.070	1.000								
(5) Openness	−0.033	0.454	0.060	−0.065	1.000							
(6) Agreeableness	0.066	0.241	0.541	−0.057	0.010	1.000						
(7) Population density	0.313	0.268	−0.053	−0.066	0.263	0.045	1.000					
(8) Manufacturing	0.495	0.090	−0.039	−0.144	−0.051	−0.023	0.109	1.000				
(9) Students	0.069	0.003	−0.100	−0.168	0.005	0.021	0.166	−0.113	1.000			
(10) R&D business (log)	0.689	0.252	−0.125	−0.230	0.101	−0.052	0.201	0.596	0.126	1.000		
(11) R&D government (log)	−0.112	−0.065	0.228	0.274	−0.249	0.317	−0.294	−0.097	0.127	0.086	1.000	
(12) R&D tertiary (log)	0.016	0.096	0.018	0.143	0.111	0.223	0.145	0.339	0.308	0.334	0.267	1.000

Notes: Covariance matrix of variables used in the split regression using regions from the lagging cluster (Table 4 column (5)). Spearman correlation coefficient results are available from the authors upon request.

Table A.6
Covariance matrix of split regression variables – leading regions (Pearson correlation).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Patents (log)	1.000											
(2) Extraversion	−0.122	1.000										
(3) Conscientiousness	−0.016	0.169	1.000									
(4) Neuroticism	−0.397	−0.421	−0.011	1.000								
(5) Openness	−0.272	0.614	−0.266	−0.061	1.000							
(6) Agreeableness	−0.075	0.059	0.298	−0.014	−0.092	1.000						
(7) Population density	−0.805	0.204	0.067	0.318	0.220	−0.093	1.000					
(8) Manufacturing	0.728	−0.101	0.146	−0.328	−0.327	0.327	−0.734	1.000				
(9) Students	−0.568	0.073	−0.054	0.367	0.289	−0.045	0.493	−0.505	1.000			
(10) R&D business (log)	0.744	−0.094	−0.184	−0.462	−0.095	−0.043	−0.673	0.500	−0.552	1.000		
(11) R&D government (log)	−0.292	−0.028	−0.023	0.270	0.158	0.000	0.061	−0.338	0.467	−0.105	1.000	
(12) R&D tertiary (log)	−0.095	−0.047	−0.222	0.180	0.290	−0.036	−0.208	−0.114	0.449	−0.032	0.761	1.000

Notes: Covariance matrix of variables used in the split regression using regions from the leading cluster (Table 4 column (6)). Spearman correlation coefficient results are available from the authors upon request.

Table A.7
REWB regressions (all regions).

		(1)
		DPMA
Years		2005–2018
Extraversion	**Within-region effects**	0.228***
Conscientiousness		0.097
Neuroticism		0.082
Openness		−0.204**
Agreeableness		−0.081
Population density		−0.694***
Manufacturing		−0.005
Students		0.001
R&D business (log)		0.113***
R&D government (log)		0.014
R&D tertiary (log)		0.072***
Extraversion	**Between-region effects**	−0.548
Conscientiousness		−0.458
Neuroticism		−0.706
Openness		−0.630
Agreeableness		1.072*
Population density		0.095
Manufacturing		3.308***
Students		0.004
R&D business (log)		0.492***
R&D government (log)		−0.029
R&D tertiary (log)		−0.122
Constant		3.758***
Random effects parameters		
Between-region variance		0.154***
Within-region variance		0.026***
N		1211

Notes: Full output of the REWB regression in specification (8) of Table 3 including the between-region effects. Patent data was obtained from the German patent office (DPMA). Significance levels: *, **, *** indicate significance at levels of 0.10, 0.05 and 0.01.

Table A.8
Regression with BF data of the Big Five project and interaction effects with cluster type.

	(1)
	Peters and Matz (2022)
Extraversion	−0.760
Intermediate region	0.000
Lagging region	7.575
Leading region	−0.079
Intermediate # Extraversion	0.000
Lagging # Extraversion	5.427***
Leading # Extraversion	−2.602
Conscientiousness	1.014
Intermediate # Conscientiousness	0.000
Lagging # Conscientiousness	−0.633
Leading # Conscientiousness	6.545*
Emotional stability	0.045
Intermediate # Emotional stability	0.000
Lagging # Emotional stability	0.042
Leading # Emotional stability	0.443
Openness	0.404
Intermediate # Openness	0.000
Lagging # Openness	−1.838
Leading # Openness	−0.145
Agreeableness	1.465
Intermediate # Agreeableness	0.000
Lagging # Agreeableness	−5.016
Leading # Agreeableness	−4.181
Population density	0.053
Manufacturing	3.965***
Students	0.002
R&D business (log)	0.441***
R&D government (log)	0.037
R&D tertiary (log)	−0.171
Constant	−6.083
N	96
R^2	0.815

Notes: Based on specification (2) in Table 3 using survey data on Big Five traits available from Peters and Matz (2022) as well as DPMA patent data and including interaction effects for the three types of regions (intermediate, lagging, leading). Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at levels of 0.10, 0.05 and 0.01.

Table A.9
Results from REWB (GSOEP) regression run on the three clusters separately.

		(1)	(2)	(3)	(4)	(5)	(6)
		DPMA	DPMA	DPMA	DPMA	DPMA	DPMA
Years		2012–2018	2012–2018	2012–2018	2012, 13, 17	2012, 13, 17	2012, 13, 17
		Intermediate	Lagging	Leading	Intermediate	Lagging	Leading
Extraversion	**Within-region effects**	0.054	0.765***	−0.130	0.011	0.654**	0.494
Conscientiousness		0.091	0.484**	0.229	0.073	0.318	0.135
Neuroticism		−0.031	0.453*	0.444*	−0.139	0.517*	0.488
Openness		−0.124	−0.587**	0.914***	0.019	−0.345	0.481
Agreeableness		0.177	−0.193	−0.159	0.189	−0.322	−0.148
Population density		3.668***	1.053	2.337**	2.936***	1.145	2.866*
Manufacturing		−4.079***	−6.348**	−6.193**	−3.215	−3.459	0.969
Students		0.007**	−0.008	−0.013**	0.010*	−0.008	−0.007
R&D business (log)		0.027	0.466***	−0.037	0.023	0.521***	0.063
R&D government (log)		0.030	0.152	0.159	0.107	0.063	0.612**
R&D tertiary (log)		0.083*	−0.003	0.702***	0.017	−0.012	0.720*
Extraversion	**Between-region effects**	−0.610	0.022	1.256	−0.762	0.053	3.127
Conscientiousness		−0.009	−0.469	1.072	−0.016	−1.710	2.395***
Neuroticism		−0.032	−0.347	−3.731	−0.253	−0.089	−2.756*
Openness		−0.309	−0.611	−4.917	−0.251	−1.066	−6.775***
Agreeableness		0.399	2.110	−7.406**	0.731	3.087**	−7.592***
Population density		0.062	0.262*	−0.165	0.165	0.262*	0.038
Manufacturing		3.966***	4.504**	1.762	4.010***	3.196	2.125***
Students		0.003	0.006	0.006	0.002	0.005	−0.005
R&D business (log)		0.294***	0.488***	0.290	0.331***	0.597***	0.499***
R&D government (log)		−0.004	0.029	−0.320	−0.038	−0.038	−0.357***

(continued on next page)

Table A.9 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
	DPMA	DPMA	DPMA	DPMA	DPMA	DPMA
Years	2012–2018	2012–2018	2012–2018	2012, 13, 17	2012, 13, 17	2012, 13, 17
	Intermediate	Lagging	Leading	Intermediate	Lagging	Leading
R&D tertiary (log)	−0.048	−0.414**	0.706	0.005	−0.430**	0.965***
Constant	3.761***	3.815***	4.055***	3.711***	3.866***	3.811***
Random effects parameters						
Between-region variance	0.125***	0.170***	0.105***	0.114***	0.168***	0.016***
Within-region variance	0.012***	0.022***	0.007***	0.012***	0.018***	0.007***
N	330	220	107	140	96	45

Notes: Based on specification (8) in Table 3, the REWB regression has been run separately for the three region types. Significance levels: *, **, *** indicate significance at levels of 0.10, 0.05 and 0.01. Cluster regressions in columns (1) to (3) contain the years 2012 to 2018; columns (4) to (6) only contain the years 2012, 2013 and 2017 in this timeframe for which GSOEP data on the Big Five is available.

Table A.10
Fixed effects regressions with EPO patent data.

	(1)
	EPO
Years	2005–2018
Extraversion	0.278*
Conscientiousness	0.060
Neuroticism	0.086
Openness	−0.280
Agreeableness	−0.171
Population density	−0.789***
Manufacturing	4.478***
Students	0.003
R&D business (log)	0.037
R&D government (log)	0.079*
R&D tertiary (log)	−0.046
Constant	5.424***
N	1197
R^2	0.262

Notes: 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 levels of 0.10, 0.05 and 0.01.

Table A.11
Fixed effects regression with lagged R&D expenditure.

	(1)	(2)
	DPMA	*DPMA*
Years	2006–2018	2007–2018
Extraversion	0.313***	0.291**
Conscientiousness	0.040	0.032
Neuroticism	0.141	0.114
Openness	−0.224**	−0.210*
Agreeableness	0.019	0.031
Population density	−1.017***	−0.986***
Manufacturing	0.124	0.316
Students	−0.001	0.000
1-yr-lag R&D business (log)	−0.065	
1-yr-lag R&D government (log)	0.017	
1-yr-lag R&D tertiary (log)	0.006	
2-yr-lag R&D business (log)		−0.043
2-yr-lag R&D government (log)		0.012
2-yr-lag R&D tertiary (log)		0.033
Constant	9.490***	9.020***
N	1123	1034
R^2	0.654	0.661

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

Table A.12
Regression at the county level.

	(1)	(2)
	Peters and Matz (2022)	Peters and Matz (2022)
Extraversion	1.648***	1.631***
Conscientiousness	−0.558	−0.756*
Neuroticism	−0.416	−0.869*
Openness	0.904*	1.274***
Agreeableness	1.243**	1.131**
Population density	0.063**	−0.002
Manufacturing	2.641***	2.294***
Students	0.000	0.000
Research-intensive sectors	0.000**	−0.000
Constant	−7.121*	−5.803
N	399	3978
R^2	0.291	0.285

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. Column (1) is based on a cross-sectional regression in 2018. Column (2) uses a random effects model with year dummies. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at levels of 0.10, 0.05 and 0.01.

Table A.13
Results from spatial regression.

	(1)	(2)	(3)	(4)
	Contiguity	Contiguity	Distance	Distance
Extraversion	0.200***	0.197***	0.224***	0.201***
Conscientiousness	0.007	0.018	0.007	0.012
Neuroticism	−0.018	−0.034	−0.013	−0.001
Openness	−0.172***	−0.163***	−0.179***	−0.178***
Agreeableness	−0.001	−0.012	0.002	−0.006
Population density	−1.080***	−1.067***	−1.045***	−1.059***
Manufacturing	0.553	0.740	0.577	0.455
Students	−0.001	−0.001	−0.001	−0.001
R&D business (log)	−0.043	−0.043	−0.023	−0.034
R&D government (log)	−0.015	−0.013	−0.011	−0.013
R&D tertiary (log)	−0.010	−0.013	−0.014	−0.012
Spatial Lags				
Extraversion	0.406**	0.447***	1.710**	1.011*
Conscientiousness	0.053		−0.835	
Neuroticism	0.329**	0.310**	1.125*	1.461***
Openness	−0.113		0.552	
Agreeableness	−0.086		0.362	
Population density	0.142		1.113	
Manufacturing	1.286		−2.674	
Students	−0.001		−0.018**	−0.010
R&D business (log)	−0.060		−0.507*	−0.382*
R&D government (log)	0.049		0.324**	0.367**
R&D tertiary (log)	−0.017		0.331	
Patents (log)	0.049		0.007	
Error term	0.242***	0.285***	0.127	0.151
N	1120	1120	1120	1120

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 levels of 0.10, 0.05 and 0.01.

Table A.14
Results from baseline regression run separately on the GDP terciles, population density (PD) terciles and BBSR regions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	DPMA Low GDP	DPMA Medium GDP	DPMA High GDP	DPMA Low PD	DPMA Medium PD	DPMA High PD	DPMA Rural region	DPMA Regions with first signs of urbanization	DPMA Urban region
Extraversion	0.479**	0.125	0.345	0.577***	0.216	0.117	0.601***	0.217	0.191
Conscientiousness	0.277	−0.056	0.144	0.089	0.114	0.080	−0.118	0.177	0.155
Neuroticism	0.133	0.107	0.139	0.099	0.007	0.019	0.036	0.047	0.149
Openness	−0.525**	−0.006	−0.112	−0.264	−0.258	−0.104	−0.375*	−0.164	−0.214
Agreeableness	0.156	−0.093	0.117	0.038	−0.059	0.118	0.195	−0.072	0.081
Population density	−0.382	−1.601**	4.493**	−0.015	0.238	−0.802	0.029	0.041	−1.021
Manufacturing	−0.676	−4.126*	0.068	−0.716	−5.473	0.185	−1.277	−1.910	0.990
Students	0.004	0.002	−0.000	0.004	−0.017**	0.002	−0.004	−0.002	0.002
R&D business (log)	0.110	−0.054	−0.054	0.015	−0.025	−0.077	−0.072	0.047	−0.027
R&D government (log)	0.012	0.015	−0.040	0.019	0.031	−0.045	0.021	0.056	−0.078
R&D tertiary (log)	−0.085	−0.031	−0.012	−0.110*	−0.065	−0.036*	−0.120**	−0.065**	−0.038*
Constant	4.801	13.592***	−21.562*	3.548	4.871	9.327	4.048	4.176	10.614
N	216	216	217	206	221	222	236	245	168
R^2	0.507	0.608	0.699	0.431	0.616	0.795	0.445	0.611	0.836

Notes: Based on specification (5) in Table 3, regressions were run separately for 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 levels of 0.10, 0.05 and 0.01.

Table A.15
Results from the lagging region subsample, regressions run separately for East and West German regions.

	(1)	(2)
	DPMA East German lagging regions	DPMA West German lagging regions
Extraversion	0.783***	0.900***
Conscientiousness	0.010	0.835**
Neuroticism	−0.288	0.402**
Openness	−0.274	−0.663***
Agreeableness	−0.056	0.261
Population density	−2.033	−2.873
Manufacturing	4.198	−3.238
Students	−0.002	0.011
R&D business (log)	0.070	0.209
R&D government (log)	−0.975**	−0.001
R&D tertiary (log)	0.125	−0.064
Constant	13.745	17.958
N	134	86
R^2	0.501	0.695

Notes: Based on specification (2) in Table 4 run separately for East and West German regions. Year and planning region fixed effects are included. Standard errors are clustered by planning region. Significance levels: *, **, *** indicate significance at levels of 0.10, 0.05 and 0.01.

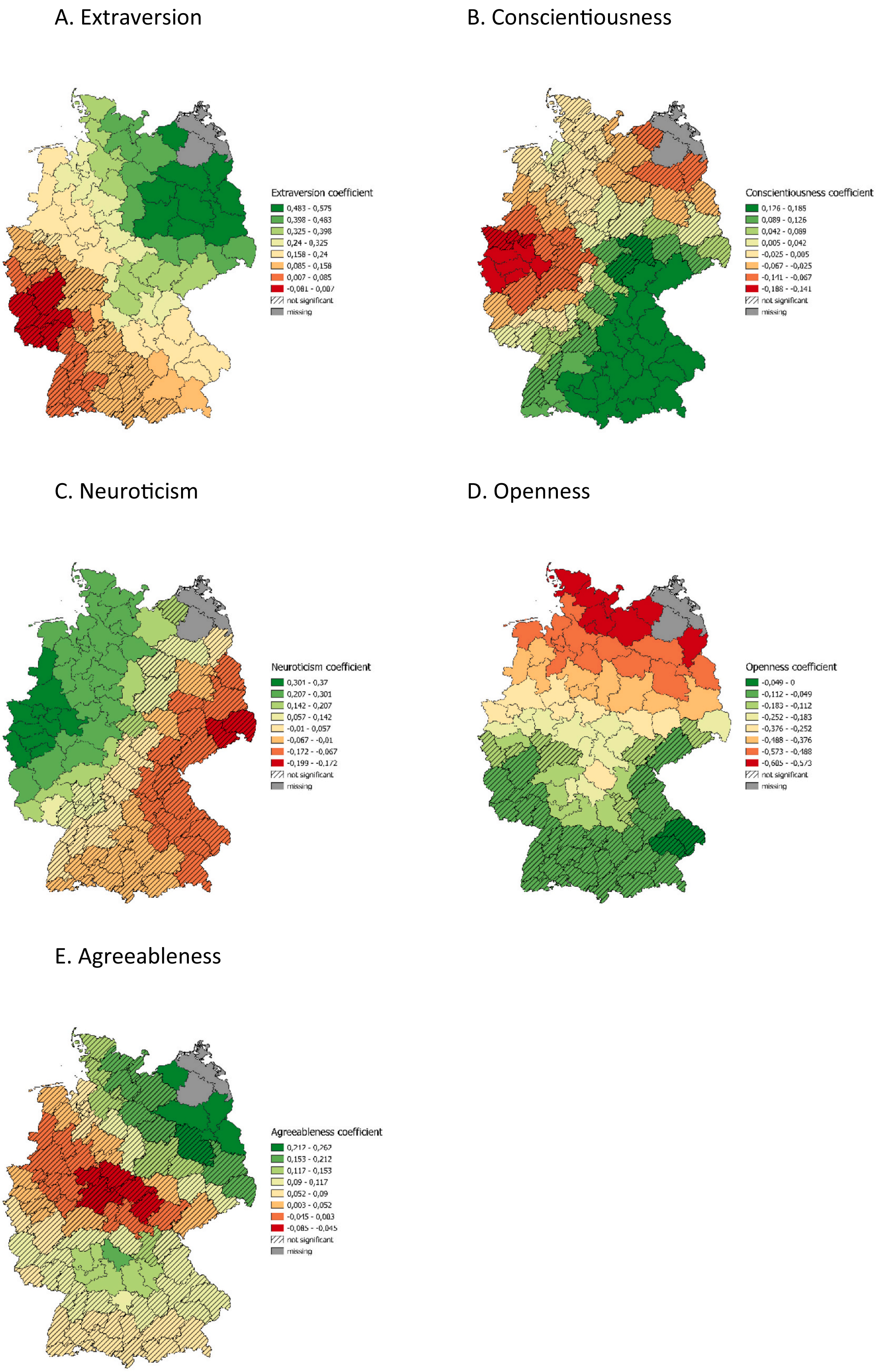

Fig. A.2. Geographically weighted panel regression
Notes: The "GWPR.light" package was used within the statistics software R. All specifications employ an adaptive bandwidth. The overall, non-locally constrained BF coefficient is statistically significant at the 5 % level in the case of extraversion (0.222) and openness (−0.228).

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