Title: Regional personality differences predict variation in COVID-19 infections and social distancing behavior

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Author Contributions

H.P., F.M.G., T.E., S.R.M., P.J.R., M.O., and S.C.M. had the initial research idea; H.P., F.M.G., T.E., and S.C.M. developed and designed research with support from S.R.M. and P.J.R.; S.D.G., D.A., and J.P. collected and preprocessed the personality data; H.P., T.E., and S.C.M. analyzed the data; H.P., F.M.G., T.E., and S.C.M. wrote the paper, and received feedback from S.R.M., P.J.R., S.D.G., M.O., and J.P.; H.P., F.M.G., and T.E. contributed equally.

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The early stages of the COVID-19 pandemic revealed stark regional variation in the spread of the virus. Combining self-reported personality data (3.5M people) with COVID-19 prevalence rates and behavioral mobility observations (29M people) in the US and Germany, we show that regional personality differences can help explain the early transmission of COVID-19; this is true even after controlling for a wide array of important socio-demographic, economic, and pandemic-related factors. We use specification curve analyses to test the effects of regional personality in a robust and unbiased way. The results indicate that in the early stages of COVID-19, Openness-to-experience acted as a risk factor while Neuroticism acted as a protective factor. The findings also highlight the complexity of the pandemic by showing that the effects of regional personality can differ (i) across countries (Extraversion), (ii) over time (Openness) and (iii) from those previously observed at the individual level (Agreeableness and Conscientiousness).

Introduction

The Coronavirus Disease 2019 (COVID-19) is a global public health emergency, reaching even the most distant corners of the world. However, some countries and – most relevant to the current paper – some regions within countries have been impacted far more severely than others^{1,2}. Such cross-regional variation has been especially pronounced during the early stages of the pandemic but continues to characterize the pandemic even as nationwide vaccination campaigns are being rolled out. Understanding the drivers of these geographical discrepancies is critical given that pandemic-related policy decisions, regulations, and interventions are implemented at the geographical (e.g., countries, states, cities, and counties) rather than the individual level^{3–7}.

Existing approaches to understanding regional differences in the impact of COVID-19 have primarily focused on socio-demographic and economic factors, such as age structure⁸, racial and ethnic composition^{9,10}, regional economic development¹¹, and income levels¹². However, even though these factors are important for understanding regional variation in COVID-19 severity, we argue that they are insufficient. As with COVID-19, the local circulation and transmission of a contagious disease in the later stages of a pandemic are often determined by factors pertaining to policies and regulations^{3,4}, or economic resources^{13–15}. In contrast, the initial outbreak of a pandemic can show substantial regional differences not just in the initial onset of cases but also in the strength of local growth and prevention behaviors in the local population. We argue that regional differences in social behaviors (i.e., the very behavior through which COVID-19 is transmitted) constitute a particularly important factor during this largely unregulated stage. With the initial outbreak of a pandemic being a particularly sensitive phase that is characterized by scarce resources yet critical in determining how well the crisis can be contained, identifying the macro-level factors that guide the social behaviors of a region's inhabitants is key to understanding and managing pandemics^{16,17}.

Drawing on theory and research in the social and behavioral sciences, we investigate the role of personality traits as a psychological determinant of the social behaviors and compliance behaviors driving the spread of infectious disease^{18,19}. We build on the widely used five-factor model²⁰ (also known as the Big Five model), which comprises five broad traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (often abbreviated as OCEAN). Individual differences in personality traits predict a range of consequential behaviors and social outcomes^{21–23}, including COVID-19-related behaviors, such as social distancing^{24–26}, compliance with hygiene rules^{26,27} and lockdown restrictions^{28–30}. While there is some variation in the findings across these studies, social distancing and compliance behaviors were generally positively associated with a person's level of Openness, Conscientiousness, Agreeableness, and Neuroticism, and negatively related to their Extraversion (see Table S1.1 for an overview of individual-level studies and findings).

These findings are largely consistent with theoretical conceptualizations and previous empirical work on the Big Five personality traits. For example, people high (vs. low) in Neuroticism tend to be hypervigilant, experience greater fear of danger and disease^{31–33}, and engage in more thorough hygienic and germ avoidance behavior^{33,34}. People high (vs. low) in Agreeableness and Conscientiousness are more likely to follow social norms, rules, and civic duties^{35,36}. And although

Openness is associated with lower germ avoidance and a tendency to deviate from cultural norms^{33,37,38}, it is also associated with global-mindedness^{39,40} and the ability to quickly adapt to novel situations^{41,42}, which could explain its role as a protective factor for individuals. Aligned with the findings that flag Extraversion as a risk factor, people high in Extraversion are highly mobile⁴³, have larger social networks^{44–46}, and tend to show lower germ aversion than people low in Extraversion³³.

However, personality traits differentiate not only people but also geographical regions⁴⁷. For example, regions with large proportions of residents who are high in Extraversion and Agreeableness display higher rates of social activity⁴⁷, and regions with large proportions of residents who are high in Openness tend to have loose social norms and high levels of social contact among strangers^{38,48}. More broadly, research in geographical psychology has established that personality traits are geographically clustered^{49,50} and that geographical variation in personality is associated with consequential political, economic, social, and health-related outcomes^{51–56}.

Understanding the impact of regional personality – in addition to individual personality – on the spread of COVID-19 is important because the response to significant threats (e.g., natural disasters) operates on the collective rather than the individual level^{57–59}. That is, major health crises (such as the COVID-19 pandemic) are likely to lead to a collective appraisal of the threat among local populations, with individuals seeking feedback and guidance from their proximal social environment on whether the threat is real and how to respond to it⁶⁰.

Prior research on pathogen prevalence suggests that regional levels of Extraversion and Openness might play a role in the spread of COVID-19^{38,61,62}. Regions with historically high rates of contagious pathogens display comparatively low levels of Extraversion and Openness. Specifically, Extraversion is low in such regions because it is associated with social behavior, and social contact heightens people's risk of contracting and transmitting contagious diseases^{33,37,38}. Openness is low because it is associated with exploration, idiosyncratic behavior, and intergroup contact with strangers, all of which increase the risk of pathogen spread^{48,63}.

Regional pathogen-prevalence theory aligns with the individual-level findings for personality and COVID-19-related behaviors reported in previous studies^{27,28,64} (see S1.1) regarding the prediction of Extraversion as a risk factor. However, the two research streams deviate in their predictions for Openness. Individual-level research suggests that Openness acts as a protective factor^{24–26,28,64} (e.g., via the ability to quickly adjust to new situations), whereas regional pathogen-prevalence work suggests that regional-level Openness can be a risk factor (e.g., via higher levels of social contact between strangers).

Such discrepancies between individual and region-level correlates are neither uncommon nor problematic. Although individual-level effects often scale up to region-level effects^{47,54,65}, it is not unusual for individual and aggregate-level analyses to diverge in their observed outcomes^{66–69}. For example, income is positively associated with political conservatism at the individual level but negatively associated with political conservatism at the state level⁷⁰. It is, therefore, possible that relationships between personality traits and COVID-19-related behaviors observed on the individual level might not translate to the geographic level.

Given that individual-level findings do not necessarily generalize to regional outcomes, we pursued a principled, exploratory approach to investigate the role of regional personality in the spread of COVID-19. Combining self-reported personality data (3.5M people) with COVID-19 prevalence rates, and behavioral mobility observations (29M people) on the country-level in the US and Germany, we examined the following two research questions: (1) Does regional personality predict regional differences in the early spread of COVID-19? And (2) Does regional personality predict regional differences in compliance with social distancing measures? Our analyses primarily focus on the early outbreak of COVID-19 (i.e., the first two months of March and April 2020), when the relevance of regional personality was likely highest. To compare the early onset directly with later developments and allow for possible changes in the impact of regional personality traits across different stages of the pandemic, we also tested the effect of regional personality on the cumulative case rates reported on September 30, 2020.

Results

To test the impact of regional personality on the spread of COVID-19, we examined both (1) the prevalence of COVID-19 in the early stages of the pandemic and (2) social distancing behaviors measured via mobility tracking. The prevalence metrics include the following three indicators: (i) COVID-19 onset (defined as case rate > 1 in 10,000 inhabitants), (ii) early COVID-19 growth rates over a 30-day period (March 15 to April 15 in the US and March 1 to April 1 in Germany), and (iii) cumulative case rates at the end of the 30-day period. To compare the effects of regional personality in the early stages of the pandemic to later developments, cumulative case rates on September 30, 2020, were included as an additional prevalence indicator. The social distancing metrics included the following two indicators that were based on objective mobility behaviors in the early stages of COVID-19: (i) time-to-adoption (calculated using change-point analyses⁷¹) and (ii) adjustment level measured as the drop in mobility following the initial adoption of social distancing.

Figure 1 provides geographical maps depicting regional variation in personality (upper row) and COVID-19 onsets, COVID-19 prevalence metrics and social distancing measures (lower row) for the US (Panel A) and Germany (Panel B). The maps display initial insights into the relationships between regional personality and COVID-19 severity (see Panel 1C for univariate correlations among these focal variables and the Supplementary Information for univariate correlations among all variables).

Figure 1. Maps of the geographical distribution of the Big Five personality traits (upper row), COVID-19 spread, and social distancing behavior (lower row) in the US (Panel A) and Germany (Panel B). We applied Getis-Ord-Gi* analysis to identify areas where high/low values of a variable geographically cluster (so-called hotspot analysis)⁷². We used a binary spatial weight matrix in which regions less than a specific threshold apart from each other were classified as proximal (i.e., 75 miles in the US and 75 kilometers in Germany). Regions with distances that exceeded this threshold were classified as distal. Panel C shows the univariate correlations between the variables displayed in Panels A and B. Colored boxes are significant

at $p < .05$. Note that the variables 6. COVID-19 Onset and 10. Social Distancing (TTA) are “time-to-event” measures where smaller values indicate an earlier occurrence of the event. Negative correlations involving these variables, therefore, indicate an increased propensity for the event occurring earlier.

The univariate relationships displayed in Figure 1 provide a first indication of the associations between regional personality and the spread of COVID-19. However, it is necessary to test these relationships more formally when controlling for potential confounding variables and spatial dependencies between geographical regions. Therefore, we tested the incremental predictive power of regional personality using Specification Curve Analysis⁷³ (SCA). This analytical framework enabled us to capture the complexity of the real world while minimizing the impact of arbitrary analytical decisions (i.e., researcher degrees of freedom). SCA is a novel approach to scientific inquiry that aims to increase the robustness of scientific findings^{73–76}. Instead of focusing on an arbitrary subset of models that could be run to test a hypothesis (e.g., with a particular method or a particular set of control variables), SCA runs all “reasonable specifications” and subsequently presents a distribution of effect sizes to provide a more realistic picture of the true effects. Hence, with a large and diverse set of established predictors and a highly complex and dynamic outcome, SCA offers a rigorous and fair test of the incremental value that any new predictor – in our case, regional personality – can add to our understanding of regional variation in COVID-19 severity.

To account for the fact that COVID-19 is determined by a broad range of factors, we calculated the effect of regional personality on the outcome variables accounting for all possible combinations ($k = 2,048$) of the following socio-demographic, economic, climatic, and pandemic-related control variables: age, gender, political orientation, educational attainment, income, industrial composition, international connectivity, tourism, health care capabilities, population density, and weather. To further establish the robustness of the results, we ran all of our analyses in the standard version of the appropriate model (e.g., linear regression or Cox proportional Hazard models) and an adaptation that included spatially lagged values of the dependent variable to account for spatial dependencies⁷⁷. This approach resulted in a total of 4,096 specifications for each personality trait and outcome. In the absence of an established gold standard, we report percentages of significant specifications for each analysis and label associations with a significant specification percentage of 70 or higher as consistent effects.

Our conservative control strategy allows us to (1) eliminate the impact of arbitrary analytical decisions, (2) rigorously test the extent to which regional personality provides incremental explanatory power above and beyond other established predictors of the spread of COVID-19, (3) illustrate the limits and boundaries of such effects, and (4) arrive at a holistic, yet nuanced, picture that does justice to the complexity of the COVID-19 pandemic.

In line with previous research in geographical psychology, we focus our interpretations (especially vis-à-vis comparisons between Germany and the US) on effect sizes rather than statistical significance alone³⁸. This decision is based on the fact that (i) sample sizes are often small and always fixed when studying geographical regions and (ii) the differences in sample size between the two countries examined here (US: 2,366 counties, Germany: 379 Stadt- und Landkreise), would result in unbalanced cross-country comparisons if purely based on statistical

significance. Instead, we directly compared the distributions of coefficients across the 4,096 specifications, which allows us to better distinguish cross-country differences that are due to differences in statistical power from those that reflect genuine differences (i.e., in the impact of regional personality and/or variation in outcome measures).

Does Regional Personality Predict Indicators of COVID-19 Prevalence?

In this section, we test the effect of regional personality on the three prevalence indicators: (1) COVID-19 onset, (2) early growth rates of COVID-19, and (3) cumulative COVID-19 case rates in the early and later stages of the pandemic.

Regional Personality Predicts COVID-19 Onset

To examine the effect of regional personality on the onset of COVID-19, we estimated time-to-event regression models separately for the US and Germany. Specifically, we used Cox proportional hazard models⁷⁸ to regress the onset dates on the five regional personality estimates using specification curve analyses (see Figure 2).

In the US (Figure 2, Panel A), regional Openness was significantly associated with earlier onsets of COVID-19 in 96% of the specifications. On average, an increase in Openness by one standard deviation was associated with a 16% increase in the risk of experiencing the initial COVID-19 outbreak on any given day ($HR = 1.16$, $SE = 0.03$, $spec_{sig} = 96\%$, $HR > 1 = 100\%$). Conscientiousness was consistently associated with earlier onsets, with 99% of the specifications being significant. On average, an increase in Conscientiousness by one standard deviation was associated with an average 15% increase in the risk of experiencing an initial outbreak of COVID-19 on any given day ($HR = 1.15$, $SE = 0.02$, $spec_{sig} = 99\%$, $HR > 1 = 100\%$). Extraversion did not show any clear patterns, with almost all specifications being non-significant ($HR = 1.01$, $SE = 0.02$, $spec_{sig} = 7\%$, $HR > 1 = 51\%$). Agreeableness was associated with earlier initial outbreaks, with 93% of the specifications being significant. An increase of one standard deviation in regional Agreeableness was associated with a 13% increase in the region's risk of experiencing an initial COVID-19 outbreak on any given day ($HR = 1.13$, $SE = 0.02$, $spec_{sig} = 93\%$, $HR > 1 = 100\%$). Finally, Neuroticism was consistently associated with later initial COVID-19 outbreaks, with 96% of specifications being significant. On average, an increase in Neuroticism by one standard deviation was associated with an average 12% decreased risk of experiencing the initial COVID-19 outbreak on any given day ($HR = 0.88$, $SE = 0.03$, $spec_{sig} = 96\%$, $HR > 1 = 0\%$).

In Germany (Figure 2, Panel B), regional personality was less strongly and less consistently related to the onset of COVID-19, which is reflected in the less extreme hazard ratios (i.e., HR different from 1). While we did not find empirical support for the role of Openness ($HR = 1.03$, $SE = 0.06$, $spec_{sig} = 9\%$, $HR > 1 = 65\%$), Conscientiousness ($HR = 0.95$, $SE = 0.05$, $spec_{sig} = 14\%$, $HR > 1 = 16\%$), and Agreeableness ($HR = 1.00$, $SE = 0.05$, $spec_{sig} = 0\%$, $HR > 1 = 49\%$), we did observe effects for both Extraversion and Neuroticism. Extraversion was

significantly related to earlier onsets in 39% of the specifications, where an increase in Extraversion by one standard deviation was associated with an average 10% increase in the risk of experiencing the initial COVID-19 outbreak on any given day ($HR = 1.10$, $SE = 0.05$, $spec_{sig} = 39\%$, $HR > 1 = 100\%$). With similar effect sizes as in the US, Neuroticism was associated with later onsets of COVID-19, with 95% of specifications being significant. An increase in Neuroticism by one standard deviation was associated with an average 14% decreased risk of experiencing the initial COVID-19 outbreak on any given day ($HR = 0.86$, $SE = 0.05$, $spec_{sig} = 95\%$, $HR > 1 = 0\%$).

Figure 2. Panels A and B: Effects of regional personality on COVID-19 onset in the US (Panel A) and Germany (Panel B) across 4,096 specifications (ordered by effect size). Effects are reported as standardized effect sizes with Hazard Ratios. $HR < 1$ indicates a later onset, while $HR > 1$ indicates an earlier onset. Error bars represent 95% Confidence Intervals. Control variables: age, gender, political orientation, educational attainment, income, industrial composition, international connectivity, tourism,

health care capabilities, population density, and weather. Positively significant effects (i.e., earlier onsets; $p < .05$) are colored in blue, negatively significant effects are colored in red (i.e., later onsets), nonsignificant effects ($p \geq .05$) are colored in grey. Panel C: Comparison of the distribution of coefficients between the US and Germany.

Regional Personality Predicts Early COVID-19 Growth Rates

To estimate the effect of regional personality on the early growth rates of COVID-19, we estimated two-stage linear regression models separately for each of the two countries. In a first step, we estimated the growth by regressing the cumulative COVID-19 cases onto time and extracted the slopes for each region. Then, in a second step, we regressed linearized versions of these growth rates onto the five regional personality estimates and all possible control variable combinations (see Figure 3).

In the US (Figure 3, Panel A), the patterns of regional personality on early growth rates largely replicated the effects observed for onsets. While there was no consistent pattern observed for Extraversion ($\beta = 0.01$, $SE = 0.02$, $spec_{sig} = 3\%$, $\beta > 0 = 65\%$), we found consistently positive effects for Openness ($\beta = 0.07$, $SE = 0.02$, $spec_{sig} = 73\%$, $\beta > 0 = 98\%$), Conscientiousness ($\beta = 0.08$, $SE = 0.02$, $spec_{sig} = 92\%$, $\beta > 0 = 100\%$), and Agreeableness ($\beta = 0.11$, $SE = 0.02$, $spec_{sig} = 97\%$, $\beta > 0 = 100\%$), with 73%, 92%, and 97% of specifications reaching significance, respectively. In contrast, regional Neuroticism was related to lower growth rates ($\beta = -0.07$, $SE = 0.02$, $spec_{sig} = 81\%$, $\beta > 0 = 3\%$), with 81% of specifications reaching significance.

In Germany (Figure 3, Panel B), the observed effects of regional personality on COVID-19 growth rates were also largely consistent with those found for onset. Extraversion was significantly associated with steeper growth rates in 47% of specifications ($\beta = 0.09$, $SE = 0.04$, $spec_{sig} = 47\%$, $\beta > 0 = 100\%$). With effect sizes similar to those observed in the US (see Figure 3, Panel C), Neuroticism was associated with flatter growth rates in 34% of specifications ($\beta = -0.06$, $SE = 0.04$, $spec_{sig} = 34\%$, $\beta > 0 = 0\%$). As before, we did not observe strong or consistent results for the other three traits, including Openness ($\beta = 0.05$, $SE = 0.05$, $spec_{sig} = 14\%$, $\beta > 0 = 87\%$), Conscientiousness ($\beta = -0.02$, $SE = 0.04$, $spec_{sig} = 10\%$, $\beta > 0 = 31\%$), and Agreeableness ($\beta = 0.06$, $SE = 0.04$, $spec_{sig} = 14\%$, $\beta > 0 = 49\%$).

Figure 3. Effects of regional personality on early COVID-19 growth rates in the 30-day time windows following March 15, 2020 in the US (Panel A), and March 1, 2020 in Germany (Panel B) across 4,096 specifications. Effects are reported as standardized effect sizes (beta). Error bars represent 95% Confidence Intervals. Control variables: age, gender, political orientation, educational attainment, income, industrial composition, international connectivity, tourism, health care capabilities, population density, and weather. Positively significant effects (i.e., steeper growth rates; $p < 0.05$) are colored in blue, negatively significant effects (i.e., flatter growth rates) are colored in red, non-significant effects ($p \geq 0.05$) are colored in grey. Panel C: Comparison of the distribution of coefficients between the US and Germany.

Regional Personality Predicts Cumulative Case Rates in the Early and Later Stages of the Pandemic

In the US (Figure 4, Panel A), the effects of regional personality on early case rates on April 15, 2020, largely replicated those observed for COVID-19 onset and early growth rates. While there was no consistent pattern observed for Extraversion ($\beta = 0.01$, $SE = 0.02$, $spec_{sig} = 1\%$, $\beta > 0 = 89\%$), we found relatively consistent positive effects for Openness ($\beta = 0.05$, $SE = 0.02$, $spec_{sig} = 50\%$, $\beta > 0 = 95\%$), Conscientiousness ($\beta = 0.04$, $SE = 0.02$, $spec_{sig} = 61\%$,

$\beta > 0 = 98\%$), and Agreeableness ($\beta = 0.08$, $SE = 0.02$, $spec_{sig} = 90\%$, $\beta > 0 = 100\%$), with 50%, 61%, and 90% of specifications reaching significance, respectively. In contrast, regional Neuroticism was related to lower growth rates ($\beta = -0.05$, $SE = 0.02$, $spec_{sig} = 64\%$, $\beta > 0 = 6\%$), with 64% of specifications reaching significance.

When contrasting the effects of regional personality on case rates in the early stages of the pandemic (April 2020) to those in the later stages (September 2020), the effects remain largely consistent in direction, but notably increase in effect size (Figure 5, Panel A). As before, Conscientiousness ($\beta = 0.12$, $SE = 0.02$, $spec_{sig} = 100\%$, $\beta > 0 = 100\%$) and Agreeableness ($\beta = 0.21$, $SE = 0.02$, $spec_{sig} = 100\%$, $\beta > 0 = 100\%$) were positively associated with case rates, while Neuroticism ($\beta = -0.18$, $SE = 0.02$, $spec_{sig} = 100\%$, $\beta > 0 = 0\%$) was negatively related to case rates, with 100% of specifications reaching significance in all three instances. While Extraversion had previously been found to positively relate to a more severe spread of COVID-19 in Germany but not in the US, it was also found to positively relate to case rates in the later stages of the pandemic in the US ($\beta = 0.06$, $SE = 0.02$, $spec_{sig} = 91\%$, $\beta > 0 = 100\%$), with 91% of specifications reaching statistical significance. The only effect that diverged in direction when compared to the early stages of the pandemic was the effect of Openness. While Openness was associated with higher case rates (as well as earlier onsets and steeper growth rates) in the early stages of the pandemic, it was significantly associated with lower case rates seven months into the pandemic in 81% of specifications ($\beta = -0.09$, $SE = 0.02$, $spec_{sig} = 81\%$, $\beta > 0 = 1\%$). As we elaborate in more detail in the general discussion, this shift might be explained by different aspects of Openness (e.g., tendency to explore, take risks, and interact with strangers, but also to quickly adjust to new situations), and by the fact that behavioral measures against the spread of COVID-19 (including social distancing and mask-wearing) became increasingly politicized in the US throughout the pandemic and might have changed the impact of Openness, which is strongly associated with political ideology ^{79–81}.

Figure 4. Effects of regional personality on cumulative case rates by April 15, 2020, in the US (Panel A) and April 1, 2020, in Germany (Panel B) across 4,096 specifications. Effects are reported as standardized effect sizes (beta). Error bars represent 95% Confidence Intervals. Control variables: age, gender, political orientation, educational attainment, income, industrial composition, international connectivity, tourism, health care capabilities, population density, and weather. Positively significant effects ($p < 0.05$) are colored in blue, negatively significant effects are colored in red, non-significant effects ($p \geq 0.05$) are colored in grey. Panel C: Comparison of the distribution of coefficients between the US and Germany.

In Germany (Figure 4, Panel B), we observed effects for Extraversion, Agreeableness and Neuroticism on early case rates on April 1. As before, Extraversion ($\beta = 0.09$, $SE = 0.05$, $spec_{sig} = 36\%$, $\beta > 0 = 100\%$) and Agreeableness ($\beta = 0.07$, $SE = 0.05$, $spec_{sig} = 26\%$, $\beta > 0 = 100\%$) were associated with higher cases rates, whereas Neuroticism was associated with lower case rates ($\beta = -0.06$, $SE = 0.04$, $spec_{sig} = 23\%$, $\beta > 0 = 0\%$). Even though these effects were found to be consistent with those observed for onsets and growth rates and similar in magnitude to those observed in the US (see Figure 4, Panel C), the smaller sample size in Germany means that they were significant in only 36%, 26%, and 23% of specifications. Neither Openness ($\beta = 0.03$, $SE = 0.05$, $spec_{sig} = 6\%$, $\beta > 0 = 79\%$), nor Conscientiousness showed strong or consistent patterns ($\beta = -0.004$, $SE = 0.05$, $spec_{sig} = 0\%$, $\beta > 0 = 46\%$).

In contrast to the US, the effects of regional personality on case rates became weaker in the later stages of the pandemic, with Conscientiousness, Agreeableness, and Neuroticism being significant in than 3%, 0% and 1% of specifications (Figure 5, Panel B). The only trait that significantly increased in effect size was Extraversion ($\beta = 0.12$, $SE = 0.04$, $spec_{sig} = 75\%$, $\beta > 0 = 100\%$), which was significant in 75% of specifications. Combined with the finding that Extraversion also significantly predicted later case rates in the US, this finding suggests that extraverted regions might have struggled to maintain social distancing in the long run. As we elaborate in more detail in the general discussion, the observation that regional personality was more predictive of case rates in later stages of the pandemic in the US but not Germany might be explained by differences in the long-term pandemic-response of the two countries. Whereas the US quickly relaxed its restrictions after initial shutdowns and put individual States in charge of social distancing and mask-wearing guidelines, Germany maintained a strict and coordinated response to managing the spread of COVID-19 throughout 2020⁸².

Figure 5. Effects of regional personality on cumulative case rates by September 30, 2020 in the US (Panel A) and Germany (Panel B) across 4,096 specifications. Effects are reported as standardized effect sizes (beta). Error bars represent 95% Confidence Intervals. Control variables: age, gender, political

orientation, educational attainment, income, industrial composition, international connectivity, tourism, health care capabilities, population density, and weather. Positively significant effects ($p < .05$) are colored in blue, negatively significant effects are colored in red, non-significant effects ($p \geq 0.05$) are colored in grey. Panel C: Comparison of the distribution of coefficients between the US and Germany.

Does Regional Personality Predict Compliance with Social Distancing Measures?

In this section, we formally test the effect of regional personality on the two social distancing indicators: (1) time-to-adoption, and (2) adjustment levels.

Regional Personality Predicts Time to Adoption

To estimate the effect of regional personality on the adoption of social distancing, we used Cox proportional hazard models⁷⁸ to regress the dates previously identified as change-points on the five regional personality estimates and different sets of control variables. In addition, we also controlled for COVID-19 onset times and growth rates in all models because the extent to which people engage in social distancing behaviors was likely impacted by the current spread of COVID-19 in a given region (see Figure 6).

In the US (Figure 6, Panel A), the effect of regional Openness, Conscientiousness, Extraversion, and Neuroticism were aligned with those observed for the indicators of early COVID-19 spread. Regional Openness and Conscientiousness were significantly associated with a later adoption of social distancing behaviors in 99.9% and 78% of specifications. On average, counties that scored one standard deviation above the mean on Openness or Conscientiousness had a 10% and 7% decreased likelihood of adopting social distancing behaviors at any given day ($HR = 0.90$, $SE = 0.03$, $spec_{sig} = 100\%$, $HR > 1 = 0\%$; and $HR = 0.93$, $SE = 0.02$, $spec_{sig} = 78\%$, $HR > 1 = 0\%$). Neuroticism was consistently associated with earlier adoption of social distancing behaviors, with 74% of specifications reaching significance. On average, an increase in Neuroticism by one standard deviation was associated with an average 7% increase in the likelihood of a region adopting social distancing on a given day ($HR = 1.07$, $SE = 0.02$, $spec_{sig} = 74\%$, $HR > 1 = 100\%$). Neither Extraversion ($HR = 1.02$, $SE = 0.02$, $spec_{sig} = 4\%$, $HR > 1 = 100\%$) nor Agreeableness ($HR = 1.01$, $SE = 0.02$, $spec_{sig} = 41\%$, $HR > 1 = 50\%$) showed strong and clear patterns, with the majority of specifications non-significant.

In Germany (Figure 6, Panel B), the effects for Openness ($HR = 0.92$, $SE = 0.06$, $spec_{sig} = 7\%$, $HR > 1 = 0\%$), Conscientiousness ($HR = 0.93$, $SE = 0.05$, $spec_{sig} = 19\%$, $HR > 1 = 0\%$), and Neuroticism ($HR = 1.09$, $SE = 0.06$, $spec_{sig} = 0\%$, $HR > 1 = 100\%$) were aligned with the findings for the early spread of COVID-19, and largely mirrored those observed in the US. However, while the effect sizes were comparable to those in the US (see Figure 6, Panel C), the majority of specifications did not reach significance due to the smaller sample size. The only trait that was significantly related to later adoption of social distancing in 70% of specifications was Extraversion. German regions that scored one standard deviation above the mean on Extraversion had an 11% decreased likelihood of adopting social distancing behaviors

at any given day ($HR = 0.89$, $SE = 0.06$, $spec_{sig} = 70\%$, $HR > 1 = 0\%$). Agreeableness was consistently but weakly related to later adoption ($HR = 0.95$, $SE = 0.06$, $spec_{sig} = 0\%$, $HR > 1 = 0\%$) and did not reach significance in any of the specifications.

Figure 6. Effects of regional personality on time-to-adoption of social distancing behaviors in the US (Panel A) and Germany (Panel B) across 4,096 specifications. Effects are reported as standardized effect sizes with Hazard Ratios. $HR < 1$ indicate a later adoption, while $HR > 1$ indicate an earlier adoption. Error bars represent 95% Confidence Intervals. Control variables: age, gender, political orientation, educational attainment, income, industrial composition, international connectivity, tourism, health care capabilities, population density, weather, COVID-19 onset, and COVID-19 growth rate. Positively significant effects (i.e., earlier onsets; $p < 0.05$) are colored in blue, negatively significant effects (i.e., later onsets) are colored in red, non-significant effects ($p \geq 0.05$) are colored in grey. Panel C: Comparison of the distribution of coefficients between the US and Germany.

Regional Personality Predicts Adjustment Level of Social Distancing

To capture the strength of the behavioral adjustment following the adoption of social distancing, we analyzed the reduction in mobility for each region following the previously defined change point. Specifically, we estimated a series of linear models regressing post-change-point levels of social distancing on the five regional personality estimates and control variables (see Figure 7).

In the US (Figure 7, Panel A), Openness ($\beta = 0.14$, $SE = 0.02$, $spec_{sig} = 100\%$, $\beta > 0 = 100\%$) and Neuroticism ($\beta = 0.06$, $SE = 0.02$, $spec_{sig} = 75\%$, $\beta > 0 = 100\%$) were associated with a stronger behavioral adjustment in social distancing, with 100% and 75% of specifications being significant, respectively. That is, an increase in Openness or Neuroticism by one standard deviation was associated with a 0.14 or 0.06 standard deviation increase in the adjustment level of social distancing. Both Conscientiousness ($\beta = -0.09$, $SE = 0.02$, $spec_{sig} = 100\%$, $\beta > 0 = 0\%$) and Agreeableness ($\beta = -0.07$, $SE = 0.02$, $spec_{sig} = 86\%$, $\beta > 0 = 0\%$) were associated with a weaker behavioral adjustment in social distancing, with 100% and 86% of specifications being significant. That is, an increase in Conscientiousness or Agreeableness by one standard deviation was associated with a 0.09 or 0.07 standard deviation decrease in the adjustment level of social distancing. Extraversion did not show any clear patterns, with most specifications being non-significant ($\beta = -0.01$, $SE = 0.02$, $spec_{sig} = 5\%$, $\beta > 0 = 23\%$).

In Germany (Figure 7, Panel B), Openness was the only trait that significantly and consistently predicted behavioral adjustment levels, with 81% of specifications being significant. Like in the US, a one standard deviation increase in Openness was associated with a 0.15 standard deviation increase in the adjustment level ($\beta = 0.15$, $SE = 0.04$, $spec_{sig} = 81\%$, $\beta > 0 = 100\%$).

Figure 7. Effects of regional personality on adjustment levels of social distancing behaviors in the US (Panel A) and Germany (Panel B) across 4,096 specifications. Effects are reported as standardized effect sizes with Hazard Ratios. $HR < 1$ indicate a later adoption, while $HR > 1$ indicate an earlier adoption. Error bars represent 95% Confidence Intervals. Control variables: international connectivity, tourism, health care capabilities, population density, latitude, age, gender, political orientation, educational attainment, income, industrial composition, COVID-19 onset, and COVID-19 growth rate. Positively significant effects (i.e., stronger adjustment; $p < .05$) are colored in blue, negatively significant effects (i.e., later onsets) are colored in red, non-significant effects ($p \geq .05$) are in grey. Panel C: Comparison of the distribution of coefficients between the US and Germany.

Discussion

Understanding how COVID-19 spreads is of paramount importance for managing the crisis and informing effective policies⁸³. The current work highlights the role of regional personality in the early outbreak of COVID-19. By combining regional personality estimates derived from over 3.4 million participants in the US and Germany with official regional COVID-19 prevalence data and geo-tagged mobility data of approximately 29 million individuals, the current project

demonstrates the importance of regional personality in a high-stakes setting and against a broad range of alternative explanations (regional demographics and political orientation, socio-economic conditions, healthcare availability, weather, and international connectivity). Inspired by calls for more robust and transparent science^{84–87}, we conducted specification curve analyses⁷³, which systematically capture the robustness and contextual sensitivity of effects through multiverse-style analyses and intuitive, holistic visualizations.

The Relationships Between Regional Personality and COVID-19

Table 1 provides an overview of the directionality and robustness of regional personality effects by country and outcome. Below we summarize and discuss the findings for each regional personality trait.

	Openness		Conscientiousness		Extraversion		Agreeableness		Neuroticism	
	US	GER	US	GER	US	GER	US	GER	US	GER
COVID onset (earlier)	++	+	++		+	+	++		--	--
Early COVID growth	++	+	++		+	+	++		--	-
Cumulative case rates (April 2020)	+					+	++	+	-	-
Cumulative case rates (September 2020)	--	+	++		++	+	++		--	
Social Distancing Time-to-adoption (later)	++		++	-		++			--	
Social Distancing Adjustment level (stronger)	++	++	--		+		--		++	

Table 1. Overview of univariate correlation results and specification curve effects of regional personality on the spread of COVID-19 and the adoption of social distancing. Effects that were significant as a univariate correlation and significant in more than 70% of specifications are denoted with double signs (++/--), effects that were significant in only the univariate correlation analyses are denoted with single signs (+/-). Effects that replicated across countries are highlighted in grey.

Openness. Consistent with prior research on pathogen prevalence theory, regional Openness was identified as a persistent risk factor in the early stages of the pandemic, with higher levels of regional Openness being related to earlier onsets of COVID-19, steeper early growth rates of cases, and delayed onset of social distancing behaviors. Importantly, however, the relationship between regional Openness and COVID-19-prevalence as well as social distancing in the US reversed over time, such that regional Openness was associated with lower cumulative case rates seven months into the pandemic and more drastic adjustments to social distancing behaviors after the delayed onset.

Although this shift might appear surprising initially, the existing literature offers various explanations for this change in directionality. One central mechanism underlying this shift might lie in the nature of the Openness trait itself. The finding that Openness was a risk factor in the early stages of the pandemic aligns with previous research indicating that open regional cultures tend to be characterized by loose social norms where rules are not enforced, and unconventional behavior is tolerated⁴⁸. Consequently, individuals in open regions are more likely to interact with strangers, take risks, and deviate from local norms^{38,47,63}. In addition, the typical lifestyle of open-minded regions (e.g., a lot of traveling and going out) might have required more substantial adjustments to social distancing measures, requiring longer lead times to implement such changes⁸⁸. However, Openness also comprises elements that explain why these tendencies could be reversed later on. For example, Openness also reflects an intellectual and reflective disposition^{89,90}, a tendency for intellectual curiosity and insight^{91,92} that might have allowed individuals to understand the necessity to change behavior as the pandemic became a scientifically acknowledged threat. In addition, Openness is associated with heightened levels of adaptability and a willingness to accept the kinds of drastic changes that may be required to change behavior^{41,42}. This, in turn, might have allowed open-minded regions to reverse the initial trend quickly and embrace social distancing more radically, once inhabitants had made the initial adjustments to their lives.

Another – albeit more speculative – explanation relates to the close ties between Openness and political ideology. In the US, the response to COVID-19 became increasingly politicized, with liberal, democratic regions responding much more aggressively to the spread of the virus than conservative, republican regions⁹³. Given that Openness is highly correlated with a liberal political ideology on both the individual^{79,80,94} and regional level^{47,81}, this political lens offers a plausible explanation for why Openness turned from a risk factor in the early stages of the pandemic into a protective factor in the later stages. The fact that we did not observe a reversal of the effect of Openness on case rates in Germany – where the response to the pandemic was much less politicized and more coordinated – provides some support for this proposition. However, our findings suggest that Openness predicts the early spread of COVID-19 and case rates on September 30, 2020, even when controlling for the political ideology of regions, and we did observe a positive effect of Openness on the adjustment levels of social distancing in Germany. Therefore, while politicization may partly explain the reversal patterns (and its stronger manifestation in the more politicized and polarized US), other mechanisms, such as the multi-faceted aspects of Openness discussed above, are likely involved as well.

Neuroticism. Regional Neuroticism was identified as a consistent protective factor, with higher levels related to a later onset of COVID-19, slower early growth in cases, an earlier adoption of social distancing behaviors, and greater behavioral adjustment. These findings align with recent research suggesting that Neuroticism is positively related to the consumption of COVID-19 related information⁹⁵, elevated safety concerns⁸⁸, and willingness to accept restrictions on quality of life²⁶. Importantly, the findings highlight the potential of regional Neuroticism to act as a protective factor in the context of major health threats and disasters. In regions where Neuroticism is high, the collective appraisal of the threat as “extremely dangerous” might result in individuals reinforcing each other by changing their habits and routines more quickly than in

emotionally stable regions. This protective role of Neuroticism at the local population level emphasizes a different side of the trait. It stands in contrast to a vast body of literature suggesting that Neuroticism is a risk factor for mental health and well-being at the individual level^{96–99}. While Neuroticism has indeed been linked to a stronger negative impact of the pandemic on individuals' mental health^{26,30,95,100–102}, our study reveals that when Neuroticism clusters in a region, it can act as a protective factor that reduces the risk of spreading a potentially lethal infectious disease.

Extraversion. The univariate correlations highlighted regional Extraversion as a potential risk factor throughout the pandemic, with earlier COVID-19 onsets, steeper initial growth rates, and a higher case rate on September 30, 2020, both in the US and Germany. While most of these associations were not affirmed by our specification curve analyses, we found that regional Extraversion was robustly associated with higher cumulative case rates in the US and slower behavioral adjustment in Germany.

Conscientiousness and Agreeableness. Regional Conscientiousness and Agreeableness produced unexpected findings in their relationship with the spread of COVID-19 and social distancing in the US (the effects for Germany were inconsistent, non-significant, and negligible with regard to effect sizes, both in the univariate correlations and the specification curve analyses). Contrary to standard conceptualizations of the traits and their empirical relationships with COVID-19-related behaviors at the individual level^{27,28,64} (see the overview of published individual-level findings in Table S1.1), Conscientiousness and Agreeableness were identified as risk factors at the regional level, showing consistent relationships to an earlier onset of COVID-19, higher initial growth rates, higher cumulative case rates, as well as a weaker (and in the case of Conscientiousness slower) adoption of social distancing measures. Close inspection of the distribution of personality traits across regions in the US (see Figure 2) suggests that Agreeableness and Conscientiousness are clustered in the Southern States, which are predominantly religious and conservative (low Openness)⁴⁹, and which have shown considerable resistance to protective measures, such as social distancing and mask compliance. The local norms to disregard the advice of health experts and to resist interference with peoples' personal liberties are likely informed by the dominant political culture⁹³. Yet, the results for Agreeableness and Conscientiousness hold even when political conservatism is accounted for in our analyses. A possible explanation for the persistent inverse relationships between Agreeableness as well as Conscientiousness and health-protective behavior is the association of the two personality traits with compliance and conformity^{35,36}. Breaking the dominant social norms of a community can have negative repercussions for an individual's relationships and broader reputation within that community. It is therefore conceivable that regions with a disproportionate number of people high in Agreeableness and Conscientiousness will exhibit greater conformity to local social norms, even when those norms run counter to the advice of health experts. Empirically testing this proposition, we ran additional analyses on a sample of 1,038 US residents collected in May 2020. Our analyses revealed that Agreeableness and Conscientiousness predicted stronger adherence to local norms and higher levels of self-community alignment, suggesting that people scoring high on these traits are more likely to follow the norms of their local communities, regardless of the content of these norms (see Supplementary Information for details).

Cross-country comparison. Across all analyses, the effects were larger and more robust in the US than in Germany, which can be explained by a number of factors. First, from a statistical perspective, the larger sample size and number of US regions included in the analyses (2,366 US counties versus 379 German administrative districts) yields greater statistical power and thus facilitates the reliable detection of statistical associations. Second, during the period examined in this study, the countries differed fundamentally in their overall response to the pandemic and their inter-regional coordination (or lack thereof). In Germany, the decision to impose strict regulations that mandated sheltering in place was a concerted national effort. By contrast, in the US, decisions about how to respond to the crisis were predominantly left to state governors and local mayors, particularly in the early days of the outbreak. As a result, the strong position of the state and local governments in the US (versus Germany) allowed for greater variation in the spread and management of COVID-19, which is also reflected in the fact that all outcomes in our study exhibit much more regional variance in the US than in Germany (see Figure 1, Panel C). In other words, the absence of evidence for effects in Germany may reveal genuine insights and important boundary conditions. This point becomes especially apparent when complementing statistical significance (which is sensitive to power) with effect sizes (which are not). Here we can see that effect sizes are similar for the US and Germany for outcomes in the earlier stages of the pandemic (see Figures 2, 3, 4, and 6) and then diverge (i.e., they become smaller in Germany and larger in the US) for outcomes in the later stages of the pandemic (see Figures 5 and 7).

As a case in point, the effects of Neuroticism in Germany only disappear for the outcomes pertaining to the later stages of the pandemic (see Table 1). This change in the predictive power of Neuroticism could be driven by the stronger, more decisive and restrictive policy response by the Merkel administration compared to the Trump administration, which may have dampened the effects of regional personality in Germany. In other words, these patterns suggest that in largely uncontained settings (i.e., the US for most of the study period and Germany for the initial outbreak), regional personality has a more distinct and clearly interpretable effect on the spread of COVID-19.

Limitations

Our research has a number of limitations. First, regional differences in testing procedures might have concealed actual regional differences in COVID-19 severity. Ideally, we would have been able to control for the number of tests in each region. However, at time of writing, no comprehensive and standardized database on testing volume at the county level exists. Instead, we partly alleviate this concern by considering multiple outcomes from different data sources (e.g., official statistics, objective behavioral mobility data and self-reported social distancing) across thousands of regions and millions of people in two different countries with different approaches to testing. In addition, we also replicate our findings for death rates (see S3.6 and S3.7), which do not share the same drawbacks of testing.

Second, recent research has highlighted the role of super-spreader events in the propagation of COVID-19¹⁰³. A single super-spreader can turn a region that is otherwise handling the crisis successfully into a pandemic hotspot. While such super-spreaders challenge the predictive power of all time-invariant variables, including regional personality, our theory still holds some insights into which regions might be particularly likely to experience super-spreader events.

Given the higher likelihood of people in extraverted and open-minded regions to socialize and gather in large groups, for example, such regions are likely to provide a more favorable turf for super-spreaders in the early stages of the pandemic. In contrast, individuals in neurotic regions might be less likely to engage with others once the word of a pandemic is spreading and preventive measures are put in place. So, while it is difficult to predict where a super-spreader might emerge, the impact of such super-spreader events on those around them is likely to be moderated by the social norms in which they are embedded.

Third, because of the limited availability of high-quality personality data, our study has been restricted to two Western, developed countries. In light of recent evidence pointing to the vast overreliance on Western data in psychological COVID-19 related research¹⁰⁴, it is crucial to acknowledge the limited cultural generalizability of our findings. As such, future research should extend the current work to other under-researched but equally severely affected world regions.

Conclusion

By integrating large-scale self-report and behavioral data, our findings show that regional personality traits offer incremental utility for understanding the current spread of COVID-19, over and above a broad array of socio-demographic, economic, structural, climatic, geo-spatial, and pandemic-related factors. Furthermore, by uncovering a previously overlooked but important driver of the early spread of COVID-19, our findings help identify regions that are at elevated risk for spreading infectious diseases. These early stages are particularly critical, as healthcare systems are often ill-equipped to respond to an unexpected outbreak with little time to adequately prepare for a surge in hospitalizations. Thus, the ability to identify regional hotspots that are at risk of spreading the disease within and outside of their local communities is essential for allocating resources and containing the transmission of the disease.

Our findings suggest that regions high in Openness (and to a lesser degree Extraversion) and low in Neuroticism are at an elevated risk of transmitting infectious diseases during this initial period and might therefore require more stringent oversight. The importance of other traits such as Agreeableness and Conscientiousness likely depends on the specific local cultural context in which personality traits are observed, highlighting both the authority and accountability of local forms of governance. Individual-level research indicates that Agreeableness and Conscientiousness are likely to lead to safe COVID-19 behaviors when studied in isolation. However, if local governance downplays the severity of the situation, the self-community alignment central to these traits may override such beneficial effects and translate into allegiances to risky policies.

Finally, the present findings caution against over-simplified answers to phenomena as complex as a global pandemic. Accordingly, we have made a deliberate effort to systematically capture, rigorously analyze and accurately report the complex dynamics that shape COVID-19 outcomes at the regional level. Our results suggest that to fully leverage the insights gained from principled analyses like ours, scientists, policymakers, and other stakeholders alike must come to terms with the “messiness” and complexity of the real world. Doing so means recognizing and

accepting the empirical fact that what works at one level of analysis might not work at another, that what works in one country might not work in every country, and that what works today might not work tomorrow.

Method

Data and Measures

Regional Personality

To estimate the personality profiles of counties in the US ($n = 2,366$) and administrative districts (Stadt- und Landkreise) in Germany ($n = 379$), we drew on large-scale self-reported personality data from the Gosling-Potter Internet Personality Project (GPIPP)¹⁰⁵, which were collected from online users between 2002 and 2015. Ethical approval for the GPIPP was obtained from the institutional review boards of the University of Texas at Austin and the University of California, Berkeley. Participants provided informed consent to their data being used for research purposes. Personality was assessed using the widely established Big Five Inventory (BFI-44)²⁰.

Our personality sample comprised 3,371,590 participants in the US (aged 15 to 70, 64.70% female, $M_{age} = 27.01$, $SD_{age} = 11.74$) and 110,029 participants in Germany (aged 15 to 70, 59.15% female, $M_{age} = 29.99$, $SD_{age} = 11.78$). In line with previous research⁴⁷, regional personality was operationalized as the average personality profile of individuals living in a specific region.

For the US, we aggregated individual-level personality scores to the level of 3,142 counties. Following previously used inclusion thresholds for the US county-level⁵⁴, we retained only those 2,513 counties with data for at least 50 participants (regional sample size for the US: $M = 1,181$; $SD = 3,176$). For Germany, we used the same cut-off of at least 50 participants and aggregated individual-level personality scores to the level of 402 administrative districts (Stadt- und Landkreise), retaining 385 geographical units (regional sample size for Germany: $M = 284$; $SD = 513$). Note that the sample sizes used in the final analyses were slightly lower because we included only units for which the full set of control variables was available. The psychometric suitability of the GPIPP data to analyze regional personality differences in the US and Germany has been demonstrated in previous work¹⁰⁶. Importantly, previous research has also shown that regional personality differences are stable over time⁵⁰. Consequently, the actual regional personality at the time of the COVID-19 outbreak should be well represented by the regional personality scores derived from the GPIPP.

COVID-19 Prevalence

Data on regional COVID-19 cases in the US and Germany were derived from reports of governmental agencies. In the US, we used data from The New York Times, which provides daily COVID-19 case numbers at the county-level based on reports from state and local health agencies¹⁰⁷. In Germany, we used data from the Robert Koch Institute¹⁰⁸, which reports the daily number of COVID-19 cases at the level of administrative districts (i.e., *Stadt- und Landkreise*).

We tested the extent to which the regional distribution of personality traits in the US and Germany predicts three important indicators of the early outbreak of COVID-19. First, we studied

the onset of the pandemic, defined as the date where the case rate in a region exceeded the threshold of 1 per 10,000 inhabitants.

Second, we studied the initial spread of the pandemic, defined as the growth rate of COVID-19 during the 30-day time windows following March 1, 2020 in Germany and March 15, 2020 in the US (see SI for an alternative specification of growth that is based on onset dates calculated for each region rather than a fixed start date). These dates approximate the onset of the exponential growth observed across the US and Germany and reflect the fact that Germany experienced a rapid rise in case rates roughly 14 days prior to the US. In Germany, the number of confirmed COVID-19 cases rose from 1,286 to 90,481 during the month of March. In the US, the number of cases rose from 2,679 to 508,872 between March 15 and April 15, 2020. These time periods were chosen to capture the critical time period when people in the US and Germany were already aware of the risk posed by COVID-19, but behaviors were not yet constrained by strict policy measures. COVID-19 growth rates were calculated by extracting the slopes of time series regression models fitted separately for each region, such that each slope captures the region's case rate as a function of time. Case rates were log-transformed prior to the analyses to account for the exponential nature of the growth curves.

Panel A of Figure 8 provides a graphical depiction of the onset and growth measures, with plots for two US counties. Eagle County, CO, was one of the earlier counties to report cases of COVID-19 and saw a relatively steep increase in cases over time (early-onset, steep slope), whereas Hamilton County, IA, had a much later onset of COVID-19 and a much slower growth (late-onset, flat slope).

Figure 8. Panel A: Case rates (cases per 1,000 inhabitants) over time. Onset times are defined as the dates where the case rates first exceeded 1/10,000. The grey band represents the time window used for the analysis of growth rates in the US. Panel B: Social distancing (tiles visited compared to February baseline). Change points were identified using a variation of the likelihood-based change point detection algorithm proposed by Hinkley⁷¹. Horizontal lines represent post-change point means (i.e., the adjustment level).

Finally, we studied cumulative case rates – that is, the number of COVID-19 cases per 1,000 inhabitants – at the end of the growth rate time window (i.e., April 15, 2020 for the US, and April 1, 2020 for Germany). We added this additional measure (which is a function of both onset and growth) to be able to compare the early stages of the pandemic to later developments. That is, we compare the effects of regional personality on cumulative case rates in April to those observed seven months into the pandemic on September 30, 2020 (the Supplementary Information includes additional analyses on death rates for the same periods).

Regional-level Social Distancing

We tested the association of regional personality estimates with objective indicators of social distancing behaviors – also referred to as physical distancing¹⁰⁹ – as an important factor impacting the spread of COVID-19. Specifically, we analyzed data provided by Facebook’s Data for Good initiative (<https://dataforgood.fb.com/>), which offers anonymized and aggregated information about the change in mobility behaviors of geographical regions around the world compared to a pre-COVID-19 baseline. The mobility metrics published by Facebook’s Data for Good Initiative are based on so-called Bing tiles, which represent small geographical areas projected onto the world. The metric used in this manuscript captures the change in the average number of tiles visited in a given day compared to a baseline calculated for each specific region before the onset of the crisis in February of 2020 (specific to the day of the week to account for weekly trends in mobility). To obtain a measure of social distancing for which higher values indicate greater levels of social distancing, we subtracted the original tiles visited metric from 0. The data made available by Facebook were aggregated to counties in the US and administrative districts in Germany. To ensure the robustness of estimates, Facebook restricted the data to regions for which at least 300 users could be tracked during the period of interest¹¹⁰.

For our analyses, we limited the time window to the period between March 1 and April 28, 2020. With about 26 million users in the US, and 3 million users in Germany, we defined two outcomes of interest: (1) The point in time at which a region saw the starkest shift in social distancing behaviors (“time-to-adoption”) and (2) the mean level of social distancing behavior after the shift in each region (“adjustment level”; see Figure S1 for distributions of the social distancing metrics across countries).

In contrast to prevalence rates, there is no clear-cut onset of social distancing behavior. We operationalized time to adoption using change point detection methods to statistically estimate the point in time that displayed the most significant “jump” in the adoption of social distancing behavior during the observed time period. Specifically, we used a variation of the likelihood-based change point detection algorithm proposed by Hinkley⁷¹, restricting the number of potential change points to one per time series. The analysis was performed with the *change point* package for R¹¹¹. Prior to the change-point detection step, we smoothed out values for weekends and the Easter holidays of each time series using locally estimated scatterplot smoothing (LOESS)¹¹². We observed a dispersed distribution of estimated change points in the US, but the variance in

adoption times was more restricted in Germany (63% of change points were located on March 17), making it more difficult to observe effects of regional personality.

Adjustment level was operationalized as the difference between a region's mobility level after the previously identified change point compared to a baseline period in February 2020. The measure reflects the degree to which a region shifted towards and settled on lower mobility levels after the initial reaction.

Panel B of Figure 8 displays social distancing in the two exemplary counties captured by (1) the point in time at which a region saw the starkest shift in social distancing behaviors, as identified by change point analysis⁷¹ ("time-to-adoption"), and (2) the mean level of social distancing behavior after the shift in each region ("adjustment level"). While Montgomery County, IA, saw a less significant change in social distancing behavior earlier on (early adoption, weak adjustment), Queens County, NY, experienced a much more significant adaptation later on (late adoption, strong adjustment).

Regional control variables

We adopted a conservative approach to testing regional personality against an extensive set of alternative predictors. This set includes various regional characteristics that are known to covary with regional personality differences and are thus customarily controlled for in psychological-geographical research, such as demographic composition, economic structure, and infrastructural setting^{47,65,113}. The set of controls also includes variables that are likely related to the spread of COVID-19 and infectious disease more generally, including a region's international connectivity, healthcare capabilities, and political orientation. Specifically, we first account for a region's socio-demographic composition (i.e., age, gender ratio, and political orientation). Second, we account for regional socio-economic differences (i.e., educational attainment, income, and industrial composition). Third, we account for pandemic-related risk factors, such as a region's international connectivity (distance to the nearest airport), tourism, and healthcare setting (i.e., physicians and hospital beds relative to population), weather (average monthly temperature) as well as population density (previously referred to as a "catch-all" variable that accounts for settlement structure and infrastructural setting^{51,114,115}). In addition to these geographical control variables, we also control for COVID-19 onset and growth rates in all models predicting the time-to-adoption and adjustment level of social distancing because social distancing behaviors are most likely co-determined by the course of the epidemic in a particular region. For example, we would expect regions hit harder by COVID-19 to follow a stricter social distancing regimen. In conclusion, we conservatively tested the effect of regional personality against a large set of alternative predictors, which were all expected to have substantial effects on the spread of COVID-19 and the adoption of social distancing behaviors. Detailed information about control variables, operationalizations, and sources for these measures can be found in the Supplementary Information.

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